MULTI-MODAL TASK INSTRUCTIONS TO ROBOTS BY NAIVE USERS

by

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PREFACE

This research was carried out at the Robotics and Intelligent Systems lab (RIS) at the University of Plymouth, U.K. The MIBL project was running from 2004–2008 and was funded by a Faculty of Technology scholarship. The project was a partly a continuation of the IBL project, that was running from 2001-2003. The motivation for this project came from the open questions in the IBL project: How can a robot be build that understands not only sequential instructions but also rules? How can a grammar be created that covers a particular domain from a corpus?

Dr. Guido Bugmann was the director of studies of this thesis and I thank him for his advice and invaluable guidance. Also, I would like to thank Dr. Paul Robinson for supervising the work and the financial support for attending conferences. I would show my appreciation to my supervisors for letting me take part in other robotics research projects during my PhD and their guidance in all areas of live.
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Plymouth, August 2008

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AUTHOR'S DECLARATION

At no time during the registration for the degree of Doctor of Philosophy has the author , Joerg Wolf, been registered for any other University award without prior agreement of the Graduate Committee.
This study was financed with the aid of a Faculty of Technology scholarship.

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1. "Industrial Robot: An International Journal, Special Issue on Service Robots Volume 32 Number 6, ISSN 0143-991X, page 499-504 , Oct 2005

and has presented papers in the following international conferences:

2. IEEE RO-MAN 08: The 17th IEEE International Symposium on Robot and Human Interactive Communication, Munich, Germany , Aug 2008.
3. the Second Workshop on Humanoid Soccer Robots @ 2007 IEEE-RAS International Conference on Humanoid Robots, Pittsburgh (USA), November 29, 2007
4. TAROS 2007: Towards Autonomous Robotic Systems Aberystwyth,U.K. ,p. 176-181, Sept 2007
5. IEEE RO-MAN 07: The 16th IEEE International Symposium on Robot and Human Interactive Communication, Special Session Paper in Human-Robot Interactive Teaching ,Jeju Island, South Korea,Paper No. WA2-4, pg. 714-719 , Sept 2007
6. IEEE RO-MAN 06: The 15th IEEE International Symposium on Robot and Human Interactive Communication, Hatfield, U.K., pg. 141-144, ISBN 1-4244-0564-5
7. European Robotics Symposium (EUROS-06), Palermo,Italy
8. Third International Conference on Computational Intelligence, Robotics and Autonomous Systems, Singapore(CIRAS) 2005, (ISSN: 0219–6131)
9. TAROS 2005: Towards Autonomous Robotic Systems, (ISBN 0-905247-03-5)
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Abstract

This thesis presents a theoretical framework for the design of user-programmable robots. The objective of the work is to investigate multi-modal unconstrained natural instructions given to robots in order to design a learning robot. A corpus-centred approach is used to design an agent that can reason, learn and interact with a human in a natural unconstrained way. The corpus-centred design approach is formalised and developed in detail. It requires the developer to record a human during interaction and analyse the recordings to find instruction primitives. These are then implemented into a robot. The focus of this work has been on how to combine speech and gesture using rules extracted from the analysis of a corpus. A multi-modal integration algorithm is presented, that can use timing and semantics to group, match and unify gesture and language. The algorithm always achieves correct pairings on a corpus and initiates questions to the user in ambiguous cases or missing information. The domain of card games has been investigated, because of its variety of games which are rich in rules and contain sequences. A further focus of the work is on the translation of rule-based instructions. Most multi-modal interfaces to date have only considered sequential instructions. The combination of frame-based reasoning, a knowledge base organised as an ontology and a problem solver engine is used to store these rules. The understanding of rule instructions, which contain conditional and imaginary situations require an agent with complex reasoning capabilities. A test system of the agent implementation is also described. Tests to confirm the implementation by playing back the corpus are presented. Furthermore, deployment test results with the implemented agent and human subjects are presented and discussed. The tests showed that the rate of errors that are due to the sentences not being defined in the grammar does not decrease by an acceptable rate when new grammar is introduced. This was particularly the case for complex verbal rule instructions which have a large variety of being expressed.

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Glossary

AI	Artificial Intelligence. A branch of computer science concerned with creating intelligence in machines.
acoustic packaging	Psychology. Acoustic information, usually in the form of speech helps infants to structure and separate "package" a stream of actions that is being demonstrated to them.
alignment	In Natural Language: use of a dialogue and sentence structure that both dialogue partners understand.
anaphora	Anaphora are references to explicitly mentioned nouns, earlier in the discourse, see Grishman (1986).
AR	Augmented Reality. Usually 3D computer graphics added to a live video feed.
BFO	Basic Formal Ontology. An ontology is a specification of a conceptualization, for example a specification how to network of semantic classes. Basic Formal Ontology is a special form for defining ontologies, see Smith (2006)
CFG	Context Free Grammar. A grammar that consists of a single non-terminal symbol on the left-hand side and terminals/non-terminals on the right hand side.
CG	see Conceptual Graphs.
Conceptual Graphs	Like semantic networks, Conceptual Graphs represent concepts and their relationships, see Sowa (2005)
context tagging	The process of tagging parts of the corpus with a context marker that describes the situation.
corpus	Latin for "body". In linguistics a corpus is a collection of texts, for example transcriptions or newspaper articles.
corpus-based robotics	Design method in robotics that allows the design of an artificial agent with natural communication skills and matching user requirements. The design method is based on collecting a corpus of instructions before implementing the agent. See (Bugmann *et al.*, 2004) or Chapter 1.
corpus-based clause grammars	Method of deriving a grammar for natural language interpretation from a corpus, see chapter 6.

DDD	determinative demonstrative deictic references: *this, these, that, those* and *the.*
DPD	determinative possessive deictic references: *my, your, our, his, her, its, their, ones.*
dependent clauses	In grammar, a clause that cannot stand alone as a sentence.
DRS	Discourse Representation Structure. The structure to represent sentences and discourse used in Discourse Representation Theory. The structure is related to predicate logic and every introduced object and referent is assigned an identifier, allowing accurate representation of anaphora..
DRT	Discourse Representation Theory. A theory to express sentences and language discourse in a formal framework. Invented by Hans Kamp, see Kamp (1993).
DTD	Document Type Definition. A DTD file defines XML tags and their syntax for a particular document type.
EPSRC	Engineering and Physical Science Research Council, a British research council
frames	In Artificial Intelligence: Frames combine domain knowledge into a structure for representing and reasoning with stereotypical concepts or situations.
GPS	General Problem Solver, problem solving A.I. program, see Newell and Simon (1972)
HCI	Human Computer Interaction, a discipline concerned with the study of the interaction between humans and computers and the design of user interfaces.
HRI	Human Robot Interaction, a discipline concerned with the study and improvement of the interaction between humans and robots.
IBL	Instruction Based Learning. IBL is the process of learning a task from a teacher through instructions, usually verbal. The learning process may be supported by, but is not depending on a demonstration.
instruction primitive	An instruction on human level, when given verbally, can be expressed using a single main verb.
instruction primitive parameter	Information further specifying an instruction, like parameters of a function in programming

instruction primitive type	Either a Conditional, Context, Action or Fact
instances	In Object-Oriented Languages / Ontology: Instantiations (“as copies”) of classes which serve as the template
KB	In Artificial Intelligence: Knowledge Base, a database that stores knowledge in an organised format. If machine-readable, deductive reasoning can be applied to the knowledge base by applying algorithms.
Lambda Calculus	In Computer Science: The Lambda Calculus is a formal system designed to investigate function definition, function application and recursion
LISP	A high level programming language, popular in artificial intelligence.
GSL	Grammar Specification Language. Language to specify grammar in the Nuance Speech Recognition system
HMM	Hidden Markov Model, a statistical model often used in temporal pattern recognition.
MIBL	Multi-modal Instruction Based Learning
multi-modal	In Human-Computer Interaction: multiple modes of input, usually including modes that go beyond the traditional mouse and keyboard.
multiple inheritance	refers to a feature of object-oriented representation in which a class can inherit behaviours and features from more than one superclass.
NLI	Natural Language Interface, an interface to a robot/computer with natural language expressions, usually by keyboard or with speech recognition.
NLTK	Natural Language Toolkit, a suite of open source Python modules, for research in natural language processing
NLU	Natural Language Understanding, the process of interpretation and making sense of natural language expressions by attaching a meaning to the natural language expression and deductive reasoning.
ontology	

	In computer science: An ontology is a specification of a conceptualization, for example a specification how to network semantic classes. Ontology is also a branch of metaphysics (philosophy) concerned with the nature of being.
OOSG	Out-of-Speech-Grammar (Error). A common error that occurs when the user attempts to express an instruction with grammar that has not been mapped to any instruction and is therefore not in its speech model.
pair-rule	In the card game Scopa: a rule that involves comparing “pairing” two cards by their value.
PCA	Principal Component Analysis, a method of reducing a data set to lower dimensions for analysis.
primitive	see Instruction Primitive
primitive verb	A finite verb in a clause indicating the Instruction Primitive
PROGRAMMAR	A parsing system which interprets the grammars written in terms of programs from Terry Winograd.
Prolog	Programming Language based on first-order logic. It is a declarative language such as SQL or LISP.
PSL	Procedure Specification Language, in IBL.
rule frame	Frame to hold information about a rule. Rules can consist of several Instruction primitives of various types.
rule instruction	In Human-Robot Interaction: an instruction, often verbal that describes a rule. Rules are distinguished from sequential instructions by having conditionals such as “if”, “only”.
Scopa	An Italian card game.
SFG	Systemic functional grammar, a model of grammar developed by Michael Halliday, see Halliday, (1976).
STR	State Transition Rule (in MIBL).
SLM	Statistical Language Model. A language model that has been generated by the statistical occurrence and word order.
syllogism	Logical argument whereby a conclusion is determined by combining statements
tautology	In logic, a tautology is a formula that is true under any possible valuation. For example ("A or not-A") is a tautology.

taxonomy	The branch of science concerned with classification. from Greek ‘taxis’ meaning ‘arrangement’
tuple	A ordered list of values. In databases often a row in a list of queried results.
unification	in logic, the combination of two terms, if one of them is not instantiated.
uni-modal	In Human-Computer Interaction: single mode of input or communication. Opposite of multi-modal.
word class	A category of words of similar form or function.

1. Introduction

1.1 Need and Aim of the research

PROVIDED the current trend in service robotics continues, service robots will become more common in our households. According to a United Nations study, (UNECE/IFR 2005a), the demand in personal and service robots will rise to 7 million units of personal robots sold within a period from 2005 to 2008. In 2007 another market survey from (World Robotics 2007) suggested that there will be 3.6 million units sold in the period from 2007 to 2010. Current service robots on the market include automated vacuum cleaners, lawn mowers and toy robots.

However, in order to expand to new areas within the household domain, robots must master much more complex tasks, such as identifying and manipulating clothes, manipulating household items and communicate efficiently. A study at the University of Plymouth by (Copleston and Bugmann 2008) showed that the most common tasks that robots should be able to do are preparing dinner, tidying and school work. However very few research groups are working on these problems.

When comparing the user's needs to what robots on the market can actually do, it can be speculated that the market in personal and service robots is driven and limited by what developers can do with robots (at the moment) rather than what users want. In order to meet the user's needs, much research is still to be done.

The motivation of this research project focuses on household robot scenarios. An important issue in the household robot scenarios is that the users of the robots are not trained operators or engineers. Therefore a service robot should be programmable by anybody interacting with them, since there are far too many possible tasks for the robot to be pre-programmed completely. Users want to adapt the robot's behaviour to their individual preference (Wermter 2003, Bugmann 2005). For example the simple task of making tea is a very personal issue, water first or tea leaves first or even milk first? How much sugar, which kind of sugar? How would a computer-illiterate elderly person teach a robot these preferences? Users may not be experts in programming. Therefore "Programming" of service robots should be done in the language of humans. "Programming" between humans is giving instructions from person to person. So there is a clear need for researching human-to-human instructions. Humans instruct (teach) by

speaking and demonstrating actions. Therefore a robot must be able to accept these instructions without the need for the instructor to change significantly his way of communicating. Users in a home environment can not be expected to read a large manual on how to use the robot. Many people would find it difficult or impossible to understand to operate a robot that has many buttons and menus. A report commissioned by the U.K. Government to Sir Claus Moser investigates basic literacy and numeracy (DfEE 1999) stated that one in five adults are functionally illiterate - that is, if given the Yellow Pages they cannot find the page for plumbers. It can be assumed that functionally illiterate people can give a robot instruction by speech and gesture in a similar way that they communicate with others. However they would be unable to deal with an un-natural complex set of instructions from a written manual or even when taught.

A natural way for humans to teach is by actions accompanied by a verbal explanation. Therefore a natural unconstrained human-robot communication interface must be *multi-modal* (spoken natural language + gestures/actions).

The instructions can include rules as well as sequential instructions. Rules, for example are "if it is raining, close the windows." How could these instructions be encoded into a robot? Is it possible such a truly natural human-robot interaction system, where the communication is unconstrained, so the user can communicate freely (free choice of vocabulary, free natural flow of gestures and speech in a limited domain) ? To the best knowledge of the author there is currently no service-robotics project with this emphasis. Other projects that have been devoted to verbal Robot Instruction systems used constrained language, which means that users have to learn specific verbal commands to instruct the robot (Crangle and Suppes, 1994; Torrance, 1994; Huffman and Laird, 1995; Matsui *et al*., 1999; Perzanowski, 2001; Iba *et al*., 2002).

The target of this PhD is to contribute to knowledge in the field of human-robot communication. More specifically **how to convert unconstrained multimodal instructions (spoken natural language + gestures/actions) into a knowledge representation usable for robot reasoning and acting**.

The investigation will build on a previous project called Instruction-Based Learning (Kyriacou, 2004; Bugmann et. al. 2004) and the idea of Corpus-Based Robotics which will be elaborated in the next sections.

1.2 Corpus-Based Robotics

A user-programmable robot must use an interface that is natural to the user. User friendliness must be the starting point of the design procedure rather than a later developed feature. Corpus-Based Robotics stands for a design procedure to completely adapt the robot to the user rather than adapting the user to the robot by training. Let's demonstrate this user centred design approach in an example. If the engineering specification is the starting point, the first verbal command an engineer would add to the robot is "go forward one thousand and two hundred millimetres". However no household user will say this command in practice. Furthermore, the engineer might conclude that there is no vision processing required to complete the task. In contrast, a user would say "get me the dirty plates from the dinning table", which may happen to be 1200 mm away from the robot. The designer using the corpus-based approach would conclude that vision is always required for a "move" command, since the user specifies the target in terms of visible objects e.g. "dirty plates, kitchen". To make robots really user-friendly and functional we must first examine how humans give commands and interact, then build a robot according to the interaction model. How to examine human interaction? In general by recording interaction. Interaction between a human teacher and a human or robotic student is recorded and investigated.

These recordings form a so called "corpus", hence the name Corpus-Based Robotics. This approach will ensure a perfect match between requirements of the user, the robots capabilities and the communication level. The design method of Corpus-Based Robotics ensures that the developer is guided towards creating a system that can understand and act upon the end-users needs, because the end-user describes his needs; this information is captured by the corpus.

Previous work carried on the "Instruction Based Learning Project" (IBL) (Kyriacou, 2004; Bugmann et. al. 2004) has shown that it is possible to extract information from a representative sample of the teacher's utterances (the "corpus") in order to:

- Identify primitive procedures that the robot has to be able to carry out i.e. the robot's "prior knowledge"
- Write and tune speech-recognition software to call and combine these primitive procedures.

This approach to the definition of the robot's functionality and natural-language interface (NLI) has been first described as "Corpus-Based Robotics" (Bugmann et. al. 2004) and is outlined in figure 1.

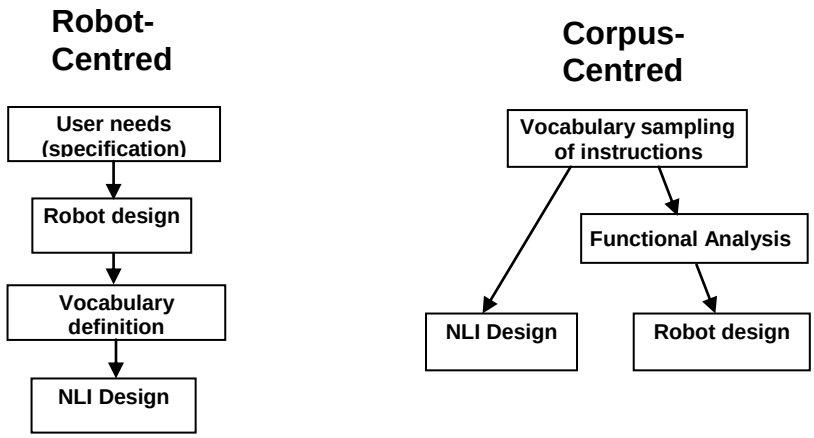


Figure 1-1: Robot vs. Corpus-Centred Natural Language Interface (NLI) design. In the Corpus-centred approach, the content of samples of instructions between humans defines at the same time the vocabulary to be dealt with by the speech interface and the required functionality of the robot. In the robot-centred approach, the functionality is defined first, then the access vocabulary, then the NLI.

By using parts of the corpus as test data while developing the system, the focus is always on the end-users demands. If the corpus is not present the developer will incorporate his own perception rather than what the users want. This can lead to incongruity between the user's need and the robots capabilities, foremost in language capabilities and in functionality and intelligence.

Corpus-Based Robotics goes further than the analysis for language interface designs. A corpus can be used to identify functions that the robot needs to be able to do.

Figure 1-2: Example of a user programmable robot.
Possible Language Primitive: pick_and_place(ddd-socks-filthy,?,+laundry)

Based on the corpus, concepts in the field of understanding task instructions for a robot can be established. These concepts aim at answering questions like:

- How to design a grammar from a multi-modal corpus?
- What knowledge representation and reasoning engine is suitable?
- What semantic structures are used in the language of the teacher?
- How to map language into a semantic representation suitable for a service robot?

These will be discussed in the next chapters.

1.2.1 From Corpus Linguistics to Corpus-Based Robotics

The idea of Corpus-Based Robotics is borrowed from Corpus Linguistics. The initial idea and the term were coined by Guido Bugmann at the University of Plymouth (Bugmann 2004). In Corpus Linguistics text is collected into a database. This collection is called "corpus". These texts can also consist of transcribed spoken dialogues. The strength of Corpus Linguistics is that the actual use of language can be investigated as opposed to the traditional study of language structure (Biber *et al*., 1998). Similarly Corpus-Based Robotics also uses a corpus to determine the language and gestures used when interaction between a human and a robot takes place.

As mentioned earlier, linguistics is divided into corpus linguistics and structural linguistics, whereby in "structural linguistics", sentences are defined from elements, the words and clear structure, the grammar. The same division could be hypothesized in robotics, where Corpus-Based Robotics is opposed to "Structural" Robotics. In Structural Robotics, the robot is build from components.

If there is an analysis of the robot's functionality based on a corpus then the logical consequence is that there is robot-function grammar. See table 1 for clarification.

TABLE I
LINGUISTICS CONCEPTS APPLIED TO ROBOT DESIGN

Symbol	Corpus	Structural
Linguistics	Corpus-Based Linguistics (has Corpus of words)	Structural Linguistics (has linguistic Grammar)
Robotics	Corpus-Based Robotics (has Corpus of functions)	Structural Robotics (has robot-function grammar)

Table 1-1: Corpus vs. Structural

For example, a part of a robot-function grammar of structural robotics could be:

```
robot ->  sensors processing_unit actuators
actuators ->  drive_electronics drive_hardware
drive_hardware ->  wheel gearbox shaft-encoder
wheel
gearbox
shaft-encoder
...
```

Whereas in corpus-based robotics, the utterance “drive forward” would create the need for a drive hardware design. The terminal symbols of this robot-function grammar are the components and software algorithms such as wheel, gearbox and shaft-encoder mentioned above. The idea of robot-function grammar can be exploited by designers to formalise and automate design. The focus of this PhD work is not robot-function grammars; even if they have been discovered here. The focus is corpus-based robotics. Robot-function grammars are worth investigating in future projects and can possibly be combined with evolutionary computing to find the optimal design of a robot, whereby the genomes are created from grammar rules to avoid impossible configurations. Grammars have been applied to related ideas such as planning a task and encoding task constraint and operation applicability into the grammar. However in the case of robot function grammars, the design and configuration of the robot is also included into the grammar.

1.3 Overview of the Thesis

The thesis starts with a review of related work in chapter 2 and earlier work in chapter 2.2. The main part of the thesis is in chronological order of the robot design and in the order of the information flow going through the robot. The flow starts with input of gesture (chapter 4), its integration with language (chapter 5), the creation of speech recognition grammars (chapter 6), and continues with reasoning and action upon those inputs (chapter 7). Finally actions that the robot produces are described in (chapter 7.8.6). Chapter 8 describes experiments and results and the thesis is concluded in chapter 9. Along the way important scientific contributions are described which advance human-robot interaction and learning. A particular focus will be true natural interaction which can only be achieved through contributions in multi-modal integration (chapter 5.3), the application of rule frames (chapter 7.3) and the formalisation of the corpus-based approach.

In a nutshell the Corpus-Based Robotics approach can be formally described as the following procedure:

Summary of Design Procedure

1. Collection of the Corpus (Chapter 3)
2. Transcription (Section 3.4) and Corpus Context tagging (Section 6.1)
3. Identification of Primitives (3.5.2, 3.5.3 and Ontology (6.2.2 , 7.4)
4. Implementation of Gesture Recognition (Section 4.1)
5. Creation of Timing Histograms for Multi-Modal Integration (Section 5.2.4)
6. Creation of Grammar (Chapter 6)
7. Implementation of Primitives, State Transition Rules and Robot Low-level Primitives (Chapter 7)
8. Dialogue Design (Chapter 7.10, 8.7.1)

Figure 1-3: Summary of the formal design procedure of Corpus-Based Robotics

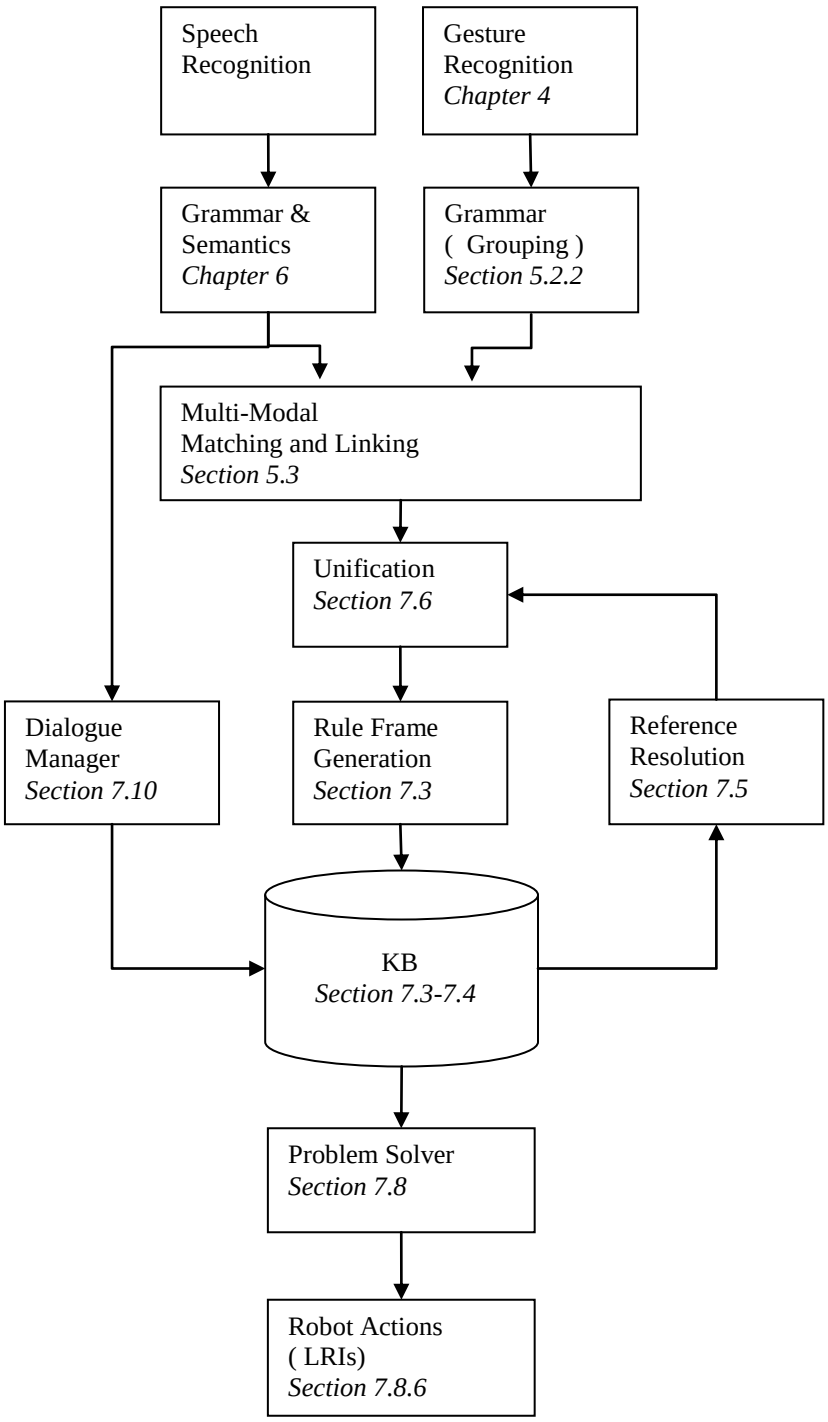


Figure 1-4: Overview of information flow in the MIBL system with Chapters of the thesis. Generally the information flow is from the inputs of Speech and Gesture at the top through to the output of "Robot Actions". This diagram gives an overview so it is easier to see how the parts described in the thesis fit together. Grammar will be described in chapter 6 while the multi-modal module will be described in chapter 5. Refer to the Chapter titles for an explanation of the modules.

1.4 Main Contributions of the Thesis

- *The Corpus-based design method*: the detailed description of the corpus-based design method which applies to robotics, but may extend to a engineering product design method (throughout thesis, Figure 3)

- *A multi-modal integration algorithm:* Includes speech-to-language pairing and unification during unconstrained free flowing interaction (sections 5.3 and 7.6)

1.5 Minor Contributions of the Thesis

1.5.1 Theoretical

- *A High level learning and reasoning engine for a service robot:* Most current service robots are only able to learn simple movement or a simple sequence of actions from a human instructor. The development of rule frames, which are a frame-based intermediate representation for human level instructions (sections 7.3, 7.4 and 7.8) are presented in this thesis as the core of the reasoning engine.
- *The application of linguistics concepts to robotics:* the discovery of robot-function grammars (section 1.2.1)
- anaphora resolution in a natural language discourse using rule frames (section 7.5)
- *A Grammar generation method:* Improves speech recognition through the application of an ontology and a clause-based grammar that fits the corpus and therefore the users most frequent utterances (section 6.4). Reduces overgeneration that can lead to nonsense translations.
- *Gesture Grammar:* Application of context free gesture grammar for grouping of gestures in order to align with the speech modality (section 5.2.3).
- *Observations on human behaviour during teaching card games and rules:* The corpus-based approach uses human behaviour to create recognition and understanding robots. The results described in chapter 8 give descriptions on how humans perform when they teach and how often they make mistakes.

- *An Investigation of out-of-grammar errors in a growing corpus-based grammar:* In a deployment test (chapter 8.8), the investigation will show that the influence of adding new grammar rules to a corpus soon loses its impact when the corpus grows to a considerable size.

1.5.2 Technical

- *An Implementation of an agent:* with associated test results (section 8.7 and 8.8)
- *A Multi-modal transcription tool (MuTra)* (section 3.4.1)
- *An annotated multi-modal corpus:* The corpus can be used for further research (section 3.5)
- *A novel method of corpus collection for Multi-modal corpora* for service robots: The use of a touch screen and not allowing direct visibility between human-to-human gestures provides a novel method of collecting data for free-flowing future human-robot interaction without the need of building the robot first.

2. On Learning in Robotic Systems and Natural Language Understanding

This chapter gives an overview of and discusses the relevant background and literature in Artificial Intelligence and Robotics. In particular natural language understanding and learning robotic systems are investigated. Initially the difference between skill and task learning is laid out and previous work on the IBL project is presented to gain an insight of the background and motivation for this PhD work.

2.1 Skill learning and Task Learning

Learning methods for teaching robots can be divided into subsymbolic skill learning and symbolic task learning.

2.1.1 Skills and Skill learning

Skill learning for a robot means refining the robots closed loop control systems that are responsible for actions. Skill learning also extends to learning to recognise salient features in sensor data. It could be summed up as learning to use the basic sensori-motor system. A typical skill learning example would be the skill to balance and walk or to pick up an object without dropping it. Most skill learning involves negative feedback systems. They may also include a model of the robot and a prediction of the consequence of its own action (Demiris and Johnson, 2003). Many skills, such as learning to balance could be described as skills that a human learns in its early years of childhood, and hence many researchers are inspired by human learning and try implementing these biologically inspired learning mechanisms in robots. This has initiated an investigation into developmental robotics (Lungarella *et al*., 2003, Asada *et al*., 2001). Recently the involvement of the motor systems during observation has become of particular interest.

Skills can be defined as the ability to use the sensori-motor system successfully.

2.1.1.1 Learning of Motor actions

Before being able to learn skills from others the robot must be able to drive its own actuators to a desired configuration. This can be achieved by feeding back information about the configuration of the robot's end effectors and compare them to the input. With this method it is possible for the robot to learn to predict the consequences of its own actions stored as a model. Using this model as an inverse it becomes a controller see (Dearden and Demiris 2005). The alternative to this pre-stage is of course to manually implement a traditional control system and to combine it with robot kinematics (McKerrow 1991).

2.1.1.2 Skill Learning by Imitation

(Schaal 1999) defines imitation learning as being concerned with three important issues: efficient motor learning, the connection between action and perception, and modular motor control in the form of movement primitives.
(Calinon and Billard 2007) use principal component analysis (PCA) in the recognition phase to identify parts of the action that is demonstrated. The learning robot from (Calinon and Billard 2007) must then generalise over multiple demonstrations. They describe learning sequential motor actions as challenging and use Hidden Markov Models (HMMs) to encode the sequential actions (patterns of motion).

2.1.2 Tasks

In this PhD work learned motor actions are defined as *action primitives* and a task can then be defined as follows:

A task can be defined as the organisation and application of skills in a sequence to fulfil a goal.

The structure of a task has an inherently symbolic nature. Evidence for that is that a task can be easier explained by verbal communication than a skill. A task such as finding a route can be explained and "learned" verbally, however how to play tennis with a racket

can not be learned verbally, especially without demonstration and imitation. Verbal communication is inherently symbolic.
A robot that is able to learn and apply tasks must previously have learned the skills. This makes skill learning a necessary foundation and therefore more important than task learning. However, to make service robots a reality, both are required and the focus of this PhD work is task learning. The skill learning processes have been minimised by the use of a touch screen rather than a camera and a humanoid robot arm.

In corpus-based robotics skills are called action primitives.
Mental skills are called knowledge primitives.

Skills can be named and listed; therefore the corpus-based robotics approach lets the robot designer identify primitives at a human level. In the IBL and MIBL scenario, these primitives are in the form of task learning rather than skill learning. There are no utterances such as "push a bit harder" which would indicate skill learning. In other scenarios, such as learning to drive a car with a driving instructor would contain many instructions of skill learning. Table 3-9 shows the identified language primitive types: fact, conditional, context, action. In a corpus containing skill learning, it is debatable if new primitive types are required, or if skill learning is part of action primitives.

An early robotic task learning system is described by (Kuniyoshi *et al*., 1994). The system extracts knowledge to learn a sequence of an assembly by observations of a human. Kuniyoshi shows how visual recognition can be segmented into an action sequence. This sequence has dependencies which are described in a hierarchical task plan. In experiments, Kuniyoshi shows how a robot learns the assembly of blocks on a table and stores all information about the task in these clean hierarchical structures. Typical for task learning systems, is the storage of usually sequential actions into hierarchical structures or frames.

2.2 Previous Work: The IBL Project

2.2.1 Introduction to the IBL Project

Previously a project on Instruction-Based Learning (IBL) was carried out at the University of Plymouth in cooperation with the University of Edinburgh (Dr. Ewan Klein). The Project was running from 2001-2004 and my PhD work, the MIBL project, is partly a continuation of this work. The IBL project focused on route instructions given to robots by naive users. A dialogue such as the following was possible between the user and a robot:

User: "Go to the University."
Robot: "How do I go there?"
User: "Take the third turning to the left..."
Robot: "Next instruction please."
User: "...take the third exit off the roundabout..."
Robot: "Next instruction please."
User: "The University will be on our right."
Robot: "OK, it's done."

The route instructions were then carried out by an 8 cm by 8 cm wide robot in a model town. The robot had an onboard camera to identify road junctions. At the beginning of the project subjects were invited to give route instructions. These instructions were audio recorded and formed the IBL corpus. The corpus contained 144 routes produced by 24 paid subjects instructing 6 routes each (Bugmann 2003). The subjects were told that a human would remote control the robot through the eyes of the onboard camera from another room.

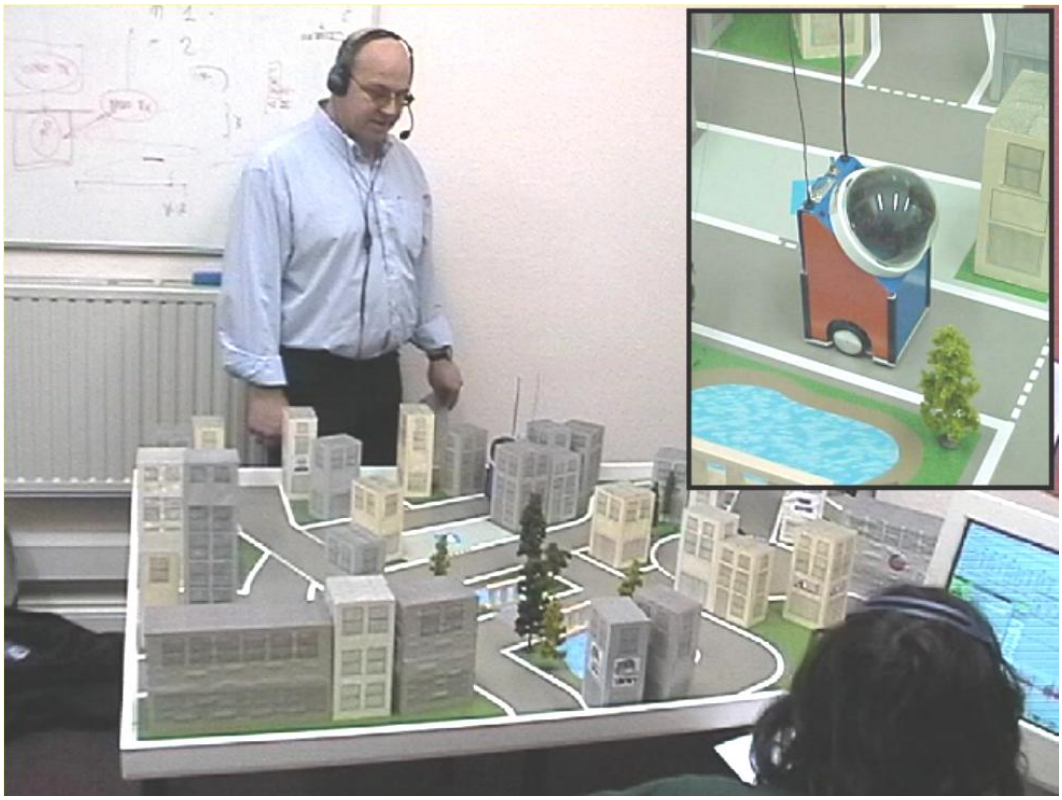


Figure 2-1: Experimental Setup of IBL: Subject giving route instructions to the mobile robot.

Using the corpus of recordings a speech recognition system was build that could recognise the route instructions and convert them into executable procedures.

2.2.2 IBL System Overview

The robot translated human instructions to robot procedures in a two stage process. First the text was converted into an intermediate semantic representation known as Discourse Representation Structure (DRS). From there the structures are mapped to robot procedures by the use of mapping rules defined in Procedure Specification Language (PSL). (Lauria *et al*., 2002).

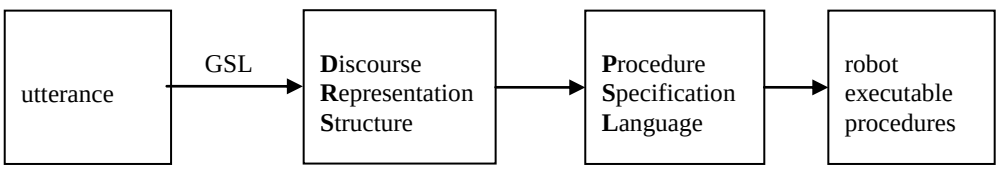


Figure 2-2: Overview of conversion process of speech to robot exec. procedures in IBL

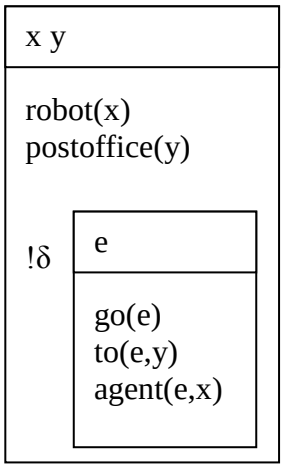
When the robot operates, the speech recognition grammar converts an utterance directly into DRS. The idea of mapping utterances directly into semantics has advantages. An

intermediate parsing stage is eliminated. Possible mismatches, at the intermediate stage that could create strings that do not make sense in semantics, are eliminated, although other problems remain.

The final grammar is in GSL (Grammar Specification Language) format. This is the format used for the Nuance[1] speech recognition software that is used in the IBL project (and in this work).

In order to create an utterance-to-DRS grammar, firstly a context-free backbone of the unification grammar is created (Bos 2002). Johan Bos created a compiler called UNIANCE that will carry out the conversion. It used syntactic features in the translation to non-terminal symbols in GSL. Terminal symbols represented the vocabulary of the corpus. Unification grammars can contain left recursive rules; however GSL only allows right recursive rules. Therefore the UNIANCE compiler eliminated left recursive rules.

The vocabulary and grammar rules have to be limited to the domain, so that speech recognition performance is increased. In order to achieve that, only the grammar rules of the context-free backbone, that were hit when parsing the IBL corpus, are used in the final grammar. The vocabulary used in the IBL corpus became the terminal symbols of the final grammar.



D={d1,d2,d3,d4,d5,d6,d7,d8}
F(possible_world)={d1,d2,d3}
F(robot)={(d1,d4),(d2,d4),(d3,d4)}
F(postoffice)={(d1,d5),(d2,d5),(d3,d5)}
F(action)={(d1,d2,d3)}
F(go_from_to)={(d2,d4,d6,d5)}
F(at_loc)={(d1,d4,d6),(d3,d4,d5)}

Figure 2-3: A graphical representation of DRS of the utterance "Go to the post office". On the left. !δ denotes that there is an action and the action is commanded. e, x, and y are discourse referents to show the dependency between the terms robot, go, to, postoffice and agent. On the right is a text representation of the same command. It shows that DRS is difficult to read.

[1] Nuance Communications, Inc., 1 Wayside Road, Burlington, MA 01803,USA (www.nuance.com) Nuance 8 and 8.5 was kindly provided by Nuance Communications for research purposes free of charge.

Discourse Representation Structures (DRS) are a well understood framework that accurately describes dependencies between the semantics and allows the interpretation of pronouns and other anaphoric expressions (Kamp and Reyle 1993). It allows representation of text in first order logic. Again the “go to the post office” example now in first order logic:

∃w ∃x ∃y (possible world(w) ^ robot(w,x) ^ postoffice(w,y)

^ ∃v ∃a (action(w,a,v)

^ ∃e (go(a,e) ^ to(a,e,x) ^ agent(a,e,y))))

While DRT is a valid semantic representation, it is not a procedure that can be carried out by a robot. In general terms DRT is more orientated at natural language structures rather than actual robot functions. In order to map this representation to a robot function (Robot Primitive) a rule base for mapping rules had to be created. The rules of this rule base are described as Procedure Specification Language (PSL). Several utterances that have different DRT representations can still have the same meaning to the robot and must therefore point to the same Robot Primitive. For instance, the expressions “take the next left, turn left, take the first turn left, etc” must all be mapped to the Robot Primitive turn(direction=”left”,ordinal=”first”) According to the final EPSRC report (Bugmann 2003) a total of approximately 200 PSL rules were required for the 15 Robot Primitives of the IBL corpus. As an example for PSL the utterance “Go to the post office” can be mapped with the following PSL rule:

event(X) &go(X) &to(X,Z) &$landmark(Z)->
go(prep =’to’; landmark = $landmark(Z))

to the Robot Primitive procedure *go(prep='to', landmark='postoffice')*

Since the IBL project was using route instructions, the resulting system was developed to deal with sequential instructions. Other forms of instructions, such as general rules, which apply at any time during the task, such as “Stop at the petrol station if you run low on petrol”, did not occur in the IBL corpus, and were therefore not investigated.

The system could not deal with conditionals, such as the one above, that were not found explicitly in the corpus (Lauria *et al*., 2002). In route instructions, sentences starting with "if" instructions are generally just a colloquial way of expressing a sequential instruction, as in the following example from the IBL corpus: "...okay if you carry on straight along this road and if you take the third left you will go over a bridge..."

Therefore, to develop a more general instruction system, there is a need for looking at a different application, where instructions not only include sequences, but also other instruction structures. In imperative programs these would be decisions and repetitions. However, in the declarative paradigm, programs consist of lists of goals and a set of rules (see e.g. PROLOG). It is unclear which paradigm is a more useful representation of human instructions. This is one of the questions that need to be addressed by analysing a new corpus of instructions in a different domain.

2.2.3 Difference between Programming by Demonstration and Instruction-based Learning

It was found that the task in the IBL project was only explained once, and in MIBL project instructions have been explained once and typically the teacher was giving a demonstration with verbal comment after. Following that, the robot / human student had understood the instructions. This is called a one-shot task learning process by (Jung H.C *et al*., 2007). Other researchers would refer to this as "Programming by Demonstration" (Dillmann *et al*., 2002). Programming by demonstration can be broadly defined as creating an generalised representation / program of a task that has been demonstrated to the robot. The robot should then be able to execute the learned task using the abstract representation (program).

Defenders of one-shot task learning, including this work argue that a service robot can only be useful and efficient if it can learn a task as fast as a grown up human, in one shot. An adult robot must have learned all basic sensori-motor skills, like a grown up human, to be able to accept one-shot learning tasks. In the robot's "childhood" it must learn its skills, such as how to move its actuators accurately, with methods described by (Demiris and Johnson 2003). A competent robot should be able to do both, "one-shot" learning and skill learning.

Let us try to give a definition of Instruction Based Learning, to distinguish better from skill learning, "Programming by Demonstration" and other approaches of robot learning:

IBL is the process of learning a task from a teacher through instructions, usually verbal. The learning process may be supported by, but is not depending on a demonstration.

Integrating these supporting demonstrations require a multi-modal system, therefore MIBL is defined as Multi-modal IBL.

2.2.4 Conclusions from the IBL Project

The IBL project concluded in the EPSRC final report (Bugmann 2003) that the domain of route instructions only included sequences and no decision making processes and loops. This led to only limited reasoning capabilities of the robot. Attempts were made to check the consistency of an explained route and also to recognise previously learned routes. A state based reasoning approach was taken allowing the robot to predict the consequences of an action, such as "turn left".

In principle the first order logic representation that DRS allowed, is a powerful mechanism for reasoning and representation of rules, as well as sequences. However the lack of grounding of the produced semantics and incompatibility with the robot functions required the translation with PSL. At this point the grounding (mapping) is made between DRS semantics and actual robot functions. However the clear structure of the lambda calculus that would enable deduction and reasoning is lost at this point.

In corpus based robotics the robot is build according to the findings of the corpus. Therefore only being able to process sequences is not a disadvantage. However the aim of generalising and researching the concept of corpus-based robotics and the translation of human instructions to robot instructions, another domain has to be investigated, where decision making and loops is significant. This is a further reason why a follow-up project started which is presented in this thesis.

The corpus-based approach aims at covering the most common expressions that the users say to the robot, and this was demonstrated in the IBL project. The project also has shown that the corpus is never complete, i.e. there are always instructions that have not been covered by the corpus and that the robot then can not deal with. This is a limitation of the corpus-based approach. In a future project, this limitations have to be investigated.

Previous research in our group focused purely on verbal instructions which are sufficient in some cases where a demonstration with physical objects is not required. In practice, many tasks are explained using a mixture of verbal instructions, gestures and demonstrations. Thus, a truly natural interface between human and robots must be multi-modal. This is one of the features included in this PhD work and has been the inspiration of the name of the project: **MIBL** (**M**ulti-**M**odal **I**nstruction **B**ased **L**earning). Multi-modal systems combine gesture and language.

Many ideas and concepts of this PhD work have their origins in the previous work. The idea of Corpus-Based Robotics and the search for language primitives are from the IBL project. Furthermore the idea of verbal communication that appears unrestricted to the user. Whereas Corpus-Based Robotics was coined during the IBL project, in this PhD work the starting point was how to formalise the idea of Corpus-Based Robotics. A major difference in architecture between the IBL and MIBL system is that utterances will be directly converted to language primitives in the grammar, rather than going through the complex DRS and PSL system. The advantage is the simplification of the process, however DRS is a powerful tool showing the relationships between semantics in an utterance and to the whole dialogue. MIBL has a more primitive reference resolution as will be shown later in Section 6.2.4, 7.5 and 7.6.

2.3 Human-Robot Interaction Robots

A general overview of Human-Robot Interaction systems can be found at Fong *et al.*, (2002) , Kiesler and Hinds (2004), Yanco and Drury (2004). However, this review will focus on Human-Robot Interaction systems which have the most similarities in philosophy and implementation to the MIBL project.
The current trend is to focus on the fundamental issues of Human-Robot interaction and general Robot learning from a developmental Robotics point of view. This trend has continued with the start of new research projects around the world. iTalk is a new project with regards to the fundamental perspective since its focus is to create a child robot with the capabilities of a 2 year old (Cangelosi 2007).

A further multi-million project that has started with possible impact on Human-Robot interaction is CoTeSys (Cognitive Technical Systems). CoTeSys explores cognition for technical systems such as vehicles, robots and factories (Buss *et al.*, 2007). The emphasis is on the incorporation of cognitive capabilities such as perception, reasoning, learning, and planning into traditional technical systems. One of the outcomes is the improvement of interaction with these systems. Buss recognises that multi-modal interaction of humans and systems which involves emotion, action and intention recognition lies at the highest and most complex levels of cognitive systems. The main aims of CoTeSys are wider, they are the technical systems will have a form of self-assessment and can therefore learn and improve themselves.

2.3.1 COGNIRON Robot Biron

COGNIRON (The Cognitive Robot Companion) is a European Union funded project that had the objective of the development of cognitive robots whose "purpose in life" would be to serve humans as assistants or "companions" (Kyriakopoulos and Siciliano, 2004). It aims at developing methods and technologies for the construction of such cognitive robots able to evolve and grow their capacities in close interaction with humans in an open ended fashion. Parts of these projects have identical objectives with the motivation behind IBL and MIBL. In particular the investigations by the COGNIRON research groups at the University of Bielefeld (Haasch *et al., 2004*) and the University of Karlsruhe (Dillmann *et al., 2002*) have relevance to this work. In the

COGNIRON project a research groups under the leadership of Kerstin Severinson Eklundh at the Royal Institute of Technology in Sweden worked on the social aspects such as the distances and orientation of the robot when giving commands (Huettenrauch et.al. 2006). A further group of COGNIRON at the University of Hertfordhire concentrates on social aspects and on how a robot can learn new skills from a human demonstrator (Saunders *et al*., 2007).

The COGNIRON project addressed a large variety of real world human-robot interaction problems and produced multiple HRI robots to carry out the research.

As part of the COGNIRON project, a group at the KTH-Sweden collected corpora on multi-modal human-robot interaction. The corpora were used to study the users behaviours (Green *et al*., 2006). As in this PhD work, they have identified the importance of user-based studies with multi-modal corpora. The results showed that users can be put into 4 types:

"Directors": actively persistively controlling the robot
"Players": interactive with the robot, passively let the robot act first
"Manipulators": also interactive with the robot, actively controlling the robot
"Pointers": little control over the robot or the environment,
adopting interaction to the situation

These user types have possible robot design implications so that the robot can adopt to the type of user. In the MIBL project, where all these types of users can easily be identified in the corpus, an adoption of the dialogue model to the user types would be useful in future work.

The University of Bielefeld, investigates multi-modal dialogues in a home tour scenario. Their robot, called BIRON, has the capability to detect which person out of a group it has to pay attention to (Haasch, A. *et al.*, 2004). The person can then engage in a simple dialogue with the robot introducing objects to the robot. (see figure 2-4). BIRON can focus microphone beams on the person thus improving speech recognition performance. The domain of the reasoning and speech recognition engine of BIRON is limited to a simple dialogue. BIRON only understands simple sentences that introduce objects, e.g.

"This is a plant". The robot has a vision system with gesture recognition and object recognition, a natural language interface and laser range finders.

Figure 2-4: Typical interaction with BIRON. "This is a plant". picture from (Haasch A *et al.*, 2004 with permission)

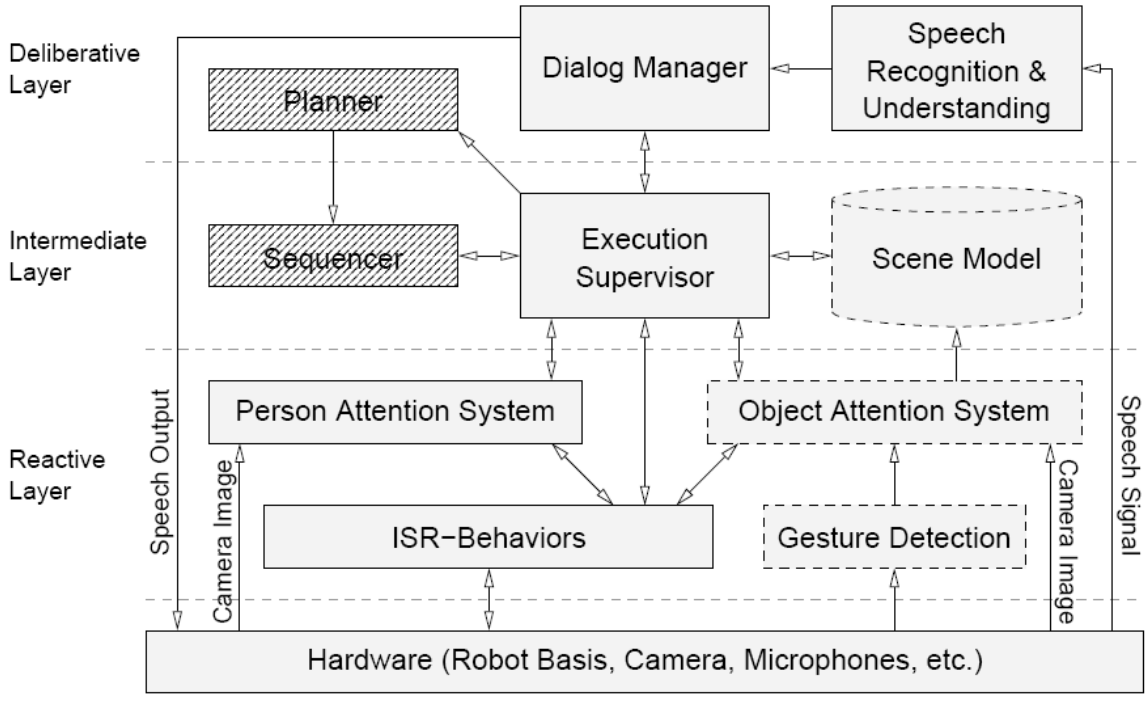


Figure 2-5: System overview of BIRON: horizontal layers in the hierarchy ensure that low level behaviour (reactive layer) continues to operate while high level plans are executed (Intermediate Layer). Speech recognition is based in the deliberative layer, since recognized sentences contain high level spoken instructions that command the robot. The layout of the architecture was inspirited by Brooks 1986. Figure from (Haasch A *et al.*, 2004 with permission).

The Bielefeld group recognized some important points which are relevant to this research:

- Combining uni-modal processing results into a multi-modal data-association framework makes the system robust against errors.
- Human communication partners can not be expected to wear special equipment such as close-talking microphone or data-gloves.
- a semantic-based grammar is necessary to extract the meaning of the sentence (parsing and subsequent interpretation is not acceptable since these kind of parser do not consider semantics and therefore introduce errors)
- missing information in an utterance can often be acquired from the scene with other sensors (Wrede *et al*., 2004)
- the system uses a horizontal hierarchy (Reactive Layer, Intermediate Layer, Deliberate Layer (see figure 4)

The research in Bielefeld concentrated on the reactive layer (Person Attention etc.). The dialogue and high-level reasoning was not investigated enough to make this service robot execute all commands necessary in its domain. This was not directly the aim of the project, the project scenario concentrated on a home tour where the service robot has just been bought and is shown around the house. The human-user introduces objects in the house to the robot. The robot understands sentences such as "This is a plant", however it might not understand sentences such as "Please water cactuses only once every fortnight and the other plants weekly". That is what people really want to tell the robot. That would be a typical household job. A corpus-based approach would potentially reveal this and this PhD work will develop the methodology of how to approach such complicated instructions.

For further reading, there is another project by Bielefeld University (Steil et. al 2004) about a robot called GRAVIS. The project concentrates on gesture recognition and learning of grasping of objects. The dialogue system is based on an investigation of a corpus of human-human and simulated human-machine dialogs. Language and gesture integration is achieved with a Bayesian network. In contrast the MIBL project tried to avoid probabilistic approaches if they are replaceable by symbolic algorithms.

2.3.2 Karlsruhe Robots

The German Collaborative Research Centre (Sonderforschungsbereich) for "Humanoid Robots - Learning and Cooperating Multimodal Robots" at the University of Karlsruhe has built two humanoid robots (Albert and ARMAR) with the target of interacting with humans in a service robot scenario (Dillmann *et al*., 2002). Their emphasis lies in building a complete system that can interact through observation and tracking of objects, gesture recognition and speech recognition. The research group recognizes that interactive programming must be a One-Shot-Learning process or it would be very annoying to the user. Another important point from the Dillmann paper is that there seem to be no system so far that integrates the control, basic interaction methods and programming techniques for humanoid robots into a single system. The robot build by the research institute can learn to fetch and carry tasks and can be taught fine manipulations of simple objects.

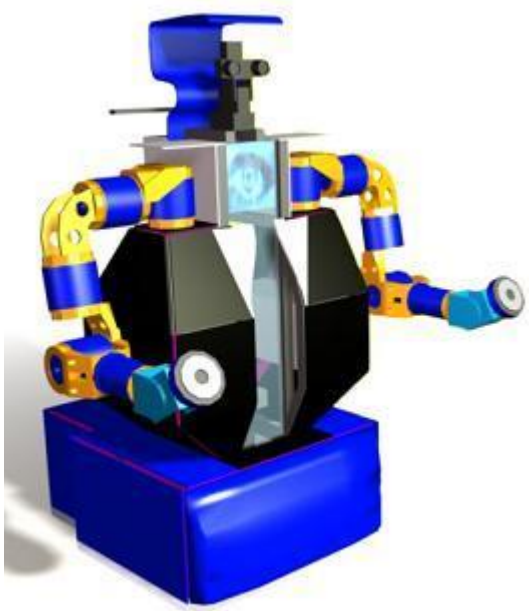


Figure 2-6: Albert 2 *(figure from Dillmann et.al. 2002, with permission)*

Figure 2-7: Humanoid Armar III : 43 degrees of freedom on a holonomic wheeled platform (figure from Asfour et.al. 2007 with permission)

Data from the recognition of trajectories and grasping is segmented so it can be broken down into a sequence in a semantic format. This system conforms with the ideas of this PhD in this respect. However sequence learning alone is not enough. For more advanced tasks, rule learning is necessary.

2.3.3 Multi-modal Human-Robot Interaction systems

Multi-modal human-robot interaction systems have been investigated by several research groups around the world (Iba *et al*., 2002; Wermter *et al.,* 2003; Dillmann *et. al.,* 2002). The challenge of multi-modal robots lies in combining the modalities to form a coherent information stream that modifies the internal model of the environment.
One of the first research projects to investigate multi-modal integration is described in Bolt's famous paper "Put-that-there" (Bolt, 1980). Bolt describes a "Media Room" with a virtual space projected against the wall, a DP-100 NEC speech recognition system and a tracking device, strapped to the users wrist. The user can point to objects on the projection and say utterances like "Create a blue square there." The system recognizes the pointing direction with the tracking device at the time the word "there" was uttered. Combining gesture and language is one of the focus points of this PhD work (Wolf and Bugmann 2006).

Multi-modal integration has also been addressed in the past by (Oviat 1999; Johansson 2001; Nigay and Coutaz, 1995 and Chai, 2003), where it is sometimes referred to as multi-modal fusion (see Djenidi *et al*., 2004). Curiously, most researchers working on multi-modal interfaces do not appear to have addressed the problem of pairing the gesture and language channels before integration. This is probably due to the fact that experiments often constrained the human-computer interaction in such a way that pairing which gesture with which language was not an issue. Constraints such as click-to-speak or limitation in computing power influence the timing of the natural flow of speech and gesture. (Oviatt *et al*., 2000) gives a good overview of multi-modal integration research projects for further reading.

Long response times of the robot/computer are often the cause of an interrupted flow of conversation. This actually simplifies the pairing problem and therefore may not have come to the attention to many other researchers. The pairing problem, especially in a free flowing conversation is therefore one of the focus points of this PhD work.

2.3.3.1 Early versus Late Fusion

The concept of early fusion interlinks the gesture recognition system with the speech recognition system at an early stage. In this case the recognition systems are usually based on the same computational model. Recently (Schillingmann *et al*., 2007) investigated Hidden Markov Models and n-gram models to generate action-specific language models, with the goal of early integration. Another computational model that incorporates the early fusion of speech recognition and vision are Semiotic Schemas (Roy, 2005). Roy showed that early fusion improves speech recognition in (Roy and Mukherjee, 2005). Early fusion models have also been used in emotion recognition; see (Wimmer *et al*., 2008).

In contrast, in the late fusion model, the fusion happens after speech recognition and gesture recognition is completed (Djenidi *et al*., 2004). In the MIBL project recognition and grouping of actions are processes that are designed to initially be independent from speech processing. This approach corresponds to the late-fusion model. It is the opinion of the author that the method of late fusion is far easier to implement, since an off-the shelf language recognition package can be used. In our case the package NUANCE 8.5. was used.

2.4 Natural Language Understanding Systems

2.4.1 A Brief Historical Overview

Literature in the areas of natural language processing and natural language understanding will be reviewed here. Major historical works include ELIZA (Weizenbaum, 1966,1976), SHRDLU (Winograd, 1971), MARGIE (Schank and Abelson, 1977). All these mentioned above use text input, rather than speech recognition. For further reading on contemporary work see (Mann, 1996; Bos 2002; Bugmann *et al*., 2004) is recommended.

2.4.2 ELIZA

ELIZA is a natural language processing system that enables a user to communicate with it via a console (Weizenbaum, Joseph.(1966)). ELIZA poses as a Rogerian psychotherapist. A Rogerian psychotherapist is very passive and understanding and lets the patient talk about their problems. Empathic understanding supposed to have psychological healing powers according to Rogers.

This is why Weizenbaum decided to make ELIZA a psychotherapist. When he was confronted with the question: "And what was it that motivated this Rogerian guise?" Weizenbaum answered:

> "From the purely technical programming point of view then, the psychiatric interview form of an ELIZA script has the advantage that it eliminates the need of storing *explicit* information about the real world."

This statement tells us that Weizenbaum recognized that "real world knowledge" i.e. semantic processing using a knowledge base is a difficult thing to implement. The program ELIZA demonstrates also that even it has no "grounded" language it can pose intelligent by replying to the user with sentences that refer to what the user said. For example if the user says "I'M DEPRESSED." , ELIZA is programmed to answer "I AM SORRY TO HEAR YOU ARE DEPRESSED" because it was programmed to do so by a simple statement along the lines of:

```
IF sentence has Subject="I" AND Verb="am" AND object="depressed"
THEN Answer="I AM SORRY TO HEAR YOU ARE DEPRESSED"
```

Even if the program only responds to key-words, the users are under the impression to be understood by ELIZA. As the example above shows, however, there is no attempt to connect the rule sets to infer new knowledge or even to ground it to the physical world. ELIZA became a very popular program, since it was one of the first attempts to imitate humanlike communication.

2.4.3 SHRDLU

SHRDLU is a program written by Terry Winograd between 1968 and 1972. It is able to understand natural language text input. He showed by this implementation, that if language is confined to a domain ("a micro world"), the computer is able to understand and act upon user requests. The micro world he chose is a table with blocks, cubes, pyramids and a box. These objects have colours and sizes assigned to them. This representation has become quite famous in A.I. under the name "Blocks World" as an idiom for simplifying a problem by restricting the complexity of the environment. It has a vocabulary of around 200 words.

Winograd recognized that syntactics, semantics and logical inference are inseparable in his PhD thesis, (Winograd, 1971). He represents knowledge as procedures, rather than as declarative statements. A procedure can make use of:

- grammar
- semantics
- deductive logic
- other procedures

As the system parses a sentence it will make use of the grammar procedures which can also call semantic interpretation procedures during the parsing process. This is a flexible and powerful method of language parsing.

This increases the flexibility of his representations, since a procedure can call and combine with any other procedures. This is the reason why Winograd has chosen to implement SHRDLU in Lisp. Lisp has the capability to ignore the difference between procedures and data.

The grammar used in SHRDLU is a form of context sensitive grammar called systemic[2] grammar. Systemic grammar helps to organize the correlation between features of natural language constituents and their semantics. This is important for understanding systems, and this was probably the reason why Terry Winograd has chosen systemic grammar. Winograd recognized that context free grammars are over-generative. The grammar rules are written in "PROGRAMMAR", a general parsing system which compiles the grammar to Lisp code. Winograd admits that it was not practical to implement the whole of systemic grammar, and that the resulting grammar is more "practical". It should be noted that the implemented grammar is not a complete valid grammar for English language. And it is definitely not a standard English grammar. However, it enables the extraction of the semantics of most sentences in order to build a natural language understanding system.

2.4.4 Schank's natural language understanding systems

In the late seventies and eighties Roger Schank developed several natural language understanding systems. Schank was working with a group of scientists (Cullingford, Rieger, Goldman, Abelson, Riesbeck, Lehnert and others) perusing the same basic ideas i.e. : creating a methodology that leads towards the eventual computer understanding of natural language (Schank and Abelson 1977).

MARGIE was one of the first parsers that created conceptual representations directly from the input text without doing an intermediate syntactic description of the sentence.

SAM (*Script Applier Mechanism*) is a natural language understanding program in the domain of stories. It is a successor of MARGIE (Schank and Abelson 1977). SAM was created by Richard Cullingford and Riesbeck in 1975.
Schank goes into great detail of what "understanding" means. To clarify the level of understanding, systems build upon his theory have, the following characteristics are given below.

[2] Systemic functional grammar (SFG) is a model of grammar developed by Michael Halliday, see (Halliday, (1976).

The system is able to:

- create a linked causal chain of conceptualizations that represent what took place in a story (a paragraph of written text).
- make inferences from the created concepts
- turn created concepts back into text in any language. (paraphrasing)

Since the programs use background knowledge the following is possible with the systems:

- Inferences can be made which are specifically mentioned from the given text.

In order to encode background knowledge of a particular context, Schank invented the idea of using "*scripts*". A *script* is a structure that describes appropriate sequences of events. *Scripts* are used if a situation has a stereotyped sequence of action. Stereotype sequences are situations that are a well known series of events. For instance in the context of a customer going shopping the following *script* could be used:

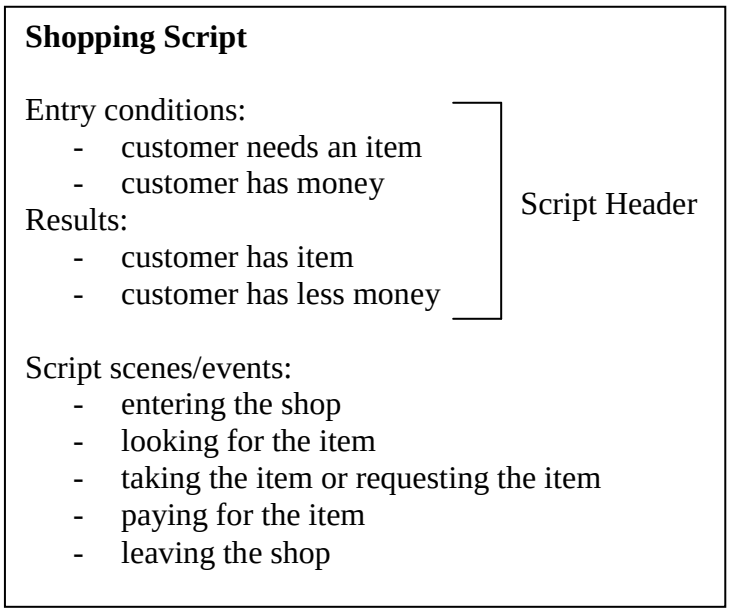


Figure 2-8: example of a script

Script items are first hypotheses of events that are going to happen in a particular situation.

The events are in an order, one event happens after another. Schank calls this a "*causal chain*". As the natural language text is processed script events are instantiated with values - a kind of slot filling. If an event happens it can enable the occurrence of another

event. In the example above: If the customer has taken an item off the shelf then the event "paying for the item" is enabled. Since a customer in a shop can only pay if there are items he/she wishes to pay for.
Unfortunately scripts only work for stereotypical situations; therefore they are by no means the answer to how to understand natural language text. Like the title of Schank's book says "Scripts, Plans, Goals and Understanding" (Schank and Abelson 1977), there are three theoretical entities necessary, namely Scripts, Plans and Goals to understand natural language.

2.4.4.1 Plans & Goals

If there is no script available, there needs to be a method of understanding a text. The first thing to do then is to identify the main "*goal*" of the entities in the text. Suppose the text starts with "John is hungry" then the goal of John is to find food. There might be several sub-goals that are identified during the processing of the text, such as going to a location where food can be found.
If a *goal* can be identified then the computer is able to:

- make prediction what might happen
- build up a script on how to achieve the goal by following the text
- put the text and word meanings in the right context (not specifically mentioned in Schank's book)

To deal with situations, that are not available as scripts, mechanisms (conceptualisations) that underlie the normal scripts must be accessed. Any conceptualizations that are instantiated must be placed so that it is possible to trace a path between them. The path is called a "*plan*". Although Schank's scripts, plans and goals idea lacks flexibility, it may be the most practical approach since a service robot is confined to a limited set of skills. Especially if a practical/commercial service robot with natural language interface would be build at present or in the near future it would most likely use a script based learning approach. Its practical nature makes it so attractive, and commercially feasible, a further reason to consider here that hopefully brings service robots closer to reality.

The programs for natural language understanding (NLU) developed by them make use of *conceptual dependency theory*. However, the inventor of *conceptual dependency theory* John Sowa argues that the implementations that Schank's research group used, does not explore the full potential of conceptual dependency (Mann 1995). For example, a word is assigned to a single meaning or word-sense where a word could have multiple meanings.

2.5 Natural Language Understanding Systems with Speech Recognition

This section reviews speech recognition architecture and tools required for natural language understanding systems with speech recognition.

2.5.1 Spoken vs. Written Language

Spoken language is different to written language. This has to be taken into account. Spoken language is more spontaneous and instant. It has a looser construction and unnecessary repetition. Often the speaker is rephrasing and stops in the middle of a sentence (Crystal 1997). On the other hand spoken language is part of a conversation, and the other parties can communicate to ask clarification questions immediately. The grammar of spoken language is different from written language, and if natural language grammar and parsers are applied they must therefore be built for spoken language. The use of formal grammar for written English was a major limitation in the IBL project. Only 60% of the corpus was covered by the grammar (Bugmann 2003).

2.5.2 Architecture

A typical Natural Language Processing System is organised in a Pipeline Architecture. The components are organised in parts that are not necessarily from the same software package. The components in order of the information flow in the pipeline are typically: speech analysis, morphological and lexical analysis, parsing, contextual reasoning, application. And from the application the pipeline can go back to speech synthesis in a similar fashion by going through utterance planning, syntactic and morphological steps to speech synthesis. Some examples are GATE (Cunningham *et al*., 1997), NUANCE 8 (Nuance App. Dev. (2005)) or the open source Natural language toolkit NLTK.

The pipeline architecture of natural language processing systems has been under criticism see (Graça *et al*., 2006; Marciniak and Strube 2005; Leidner 2003; Daelemans and van den Bosch 1998), however it is still the most common structure since it is the best method to implement a natural language system from a software engineering point of view. Also the natural language system introduced in this PhD work will use the pipeline architecture. There is no escape from it. The criticism is mainly aimed at the

problems introduced by the possibly independent language tools that are used in a chain. It is hard to give feedback to a previous stage and due to the transformations from stage to stage information may be lost and errors may therefore be introduced. One of these pipeline tools is typically a syntactic parser that parses recognised text. These parsers are often not trained on the specific context of the domain and therefore introduce errors.

2.5.3 Hidden Markov Models

Modern speech recognition systems utilise Hidden Markov Models (HMM) to recognise phonemes, words and phrases in a multi-layered model (Cunningham 2000). HMMs, in the context of speech recognition, are statistical models of how likely a word follows another. Or at a lower level, which phoneme or acoustic feature most likely follows another. A common way to extract acoustic features is by using Fast-Fourier Transforms. The acoustic features and the probably of their occurrence are an inheritably sub-symbolic (statistical) process. For a good introduction see (Rabiner 1989). However these models use symbolic building blocks: phonemes, words and phrases. Their relations are expressed as grammar. The HMM returns the most likely interpretation (with the highest overall probability in the markov chain). By accepting this as the interpretation text, the sub-symbolic audio data has become a text.

2.5.4 Interpretation

In case of natural language understanding, where the emphasis is on understanding, the text alone is not sufficient. The concept of "understanding" puts the text to a meaning, a relation that the robot can reason with, and particularly important, the concept of "understanding" means that the text and relations the robot reasons with are connected in the robots action and perception. Therefore the grammar is connected to an interpretation (called interpretation grammar (Nuance App. Dev. (2005)), slot filling or semantic grammar (Rosner and Johnson (1992)), which is usually expressed as an attachment to a grammar rule. Grammar acts as the defining language to connect speech to semantic interpretation.

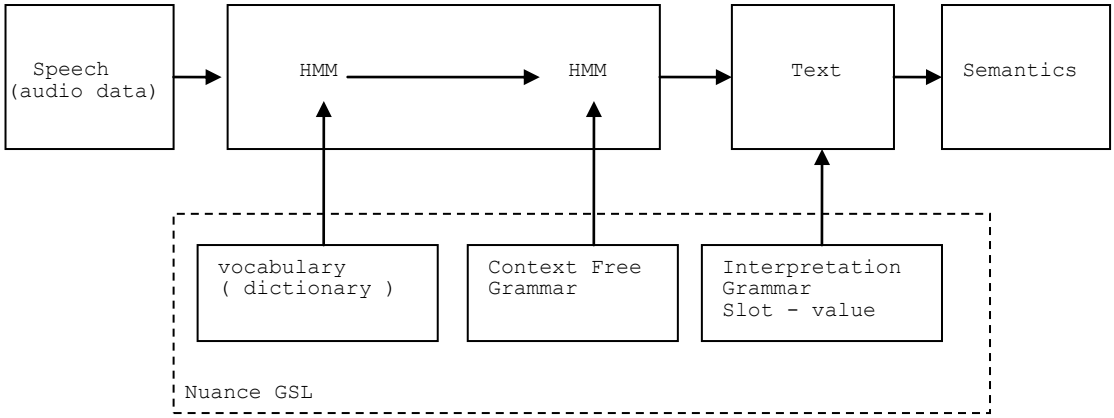


Figure 2-9: A typical Natural Language Interpretation system uses grammar to define multi-layered HMM models from phonemes to words and words to sentences. These models serve as mapping between Speech and text. Traditionally the text output is parsed (syntactic analysis) by a interpretation grammar to determine the meaning of the text

2.5.5 Grammar

The Nuance speech recognition system, used in this project, combines the CFG (context free grammar) and the interpretation grammar into one. Every CFG grammar rule can have slot-and-value semantics attached to it. Parsing recognised text to extract an interpretation has been widely criticised for the same reason as the pipelining architecture, because the grounding of the interpretation is disconnected from the text and speech recognition that are preceding in the pipeline. In practice this means that text is recognised that the robot cannot understand because it does not make sense. One of the problems with IBL was that it recognises "turn the tree", which is correct in English but does not make sense. It was introduced by generalising a CFG from sentences like "pass the tree" and "turn left".

The CFG grammar in this case is:

```
S   →V NP
S   →V ADJ
NP  →DET N
DET →the
N   →tree | corner
V   →turn | pass
ADJ →left
```

Disconnecting meaning from grammar, such as in this case, produces unwanted overgeneration. A correct syntax does not always lead to sentences meaningful within the domain of correspondence of the robot.

Chapter 6 describes how the combination of CFG and interpretation is used as an advantage to improve speech recognition. In a nutshell, the combination allows the prevention of unwanted generalisation by abstracting syntax rules from the corpus.

2.6 Semantic Representation Theories

2.6.1 Semiotic Schemas

In an effort to create a non-symbolic (computational) system that can make the connection to symbols, Deb Roy from MIT created a framework (Roy 2005), which is outlined here. The framework for semiotic schemas is built upon creating a meaning from sensor data and motor acts. It is therefore a so called bottom-up approach to machine learning systems. Every piece of knowledge stored in the robots "brain" can be referred back to the physical world through sensor data and motor acts. It is a grounded system. The knowledge can also be used to make predictions about the future and compare these to actual sensations.

This is called an *analog belief*. So sensors are mapped to *analog beliefs*. See the notation below in figure 2-10.

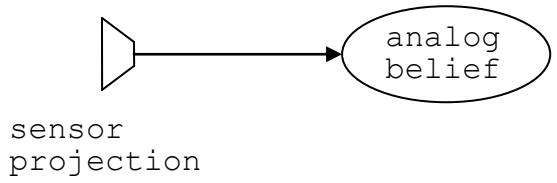


Figure 2-10: a sensor (natural sign) is monitored to create an "average" belief state

One may wonder how this "analogue" statistical distributions can be put into categories. Deb Roy introduces categorizers as a link between analog beliefs and discrete *categorical beliefs*. In the graphical notation analog beliefs are oval and categorical beliefs are rectangular.

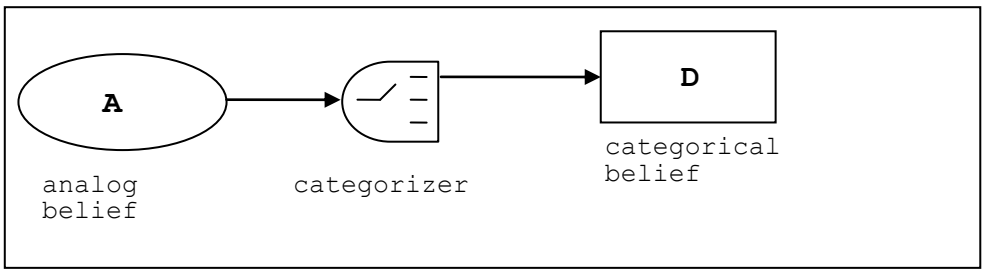


Figure 2-11: a categorizer makes discrete decisions based on an analog belief

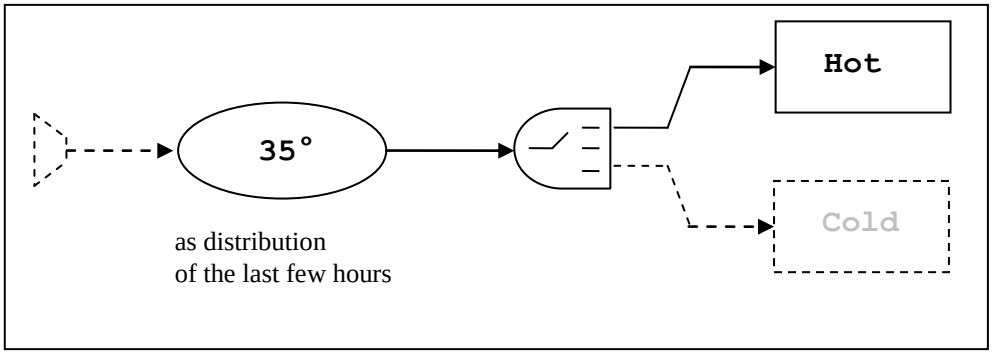


Figure 2-12: a robot that can feel temperature and belief if it is hot or cold

Deb Roy implemented this framework into a robot called Ripley, which has a 7 degrees of freedom arm, vision system and a speech interface. The robot was designed for grounded language experiments (Roy *et al*., 2004). The framework is an attempt to connect the symbolic world of language to the non-symbolic world of sensors and actuators. Roy argues that not-grounded systems would need a human in the loop during design and implementation to connect sensor data to a representation system in the robot, whereas his approach enables statistical mapping between the sensors/actuators and the introduced symbols. The framework of semiotic schemas is used as an inspiration to this work. The most relevant concept for here is the idea that physically grounded analogue data can be converted to symbolic categories. Categorical believes could be used to represent locations of cards and the recognised actions/gestures. This allows symbolic processing and the integration of language into the robots advanced reasoning system, even though the robots low level AI (skill-learning and pattern recognition) is subsymbolic.

2.6.2 Conceptual Graphs

Conceptual Graphs (CG) are related to semantic networks. They were invented by John F. Sowa. Conceptual Graphs can represent concepts and their relationships. They are a powerful tool to create a knowledge base. CGs have the following useful properties: They are human readable (hence they can be turned into natural language expressions. They can be created from natural language expressions. They can be turned into predicate logic statements (with certain constrains).Conceptual graphs are best explained by an example. Below an example of the sentence:
“John is going to Boston by bus” taken from (Sowa J.F. website)

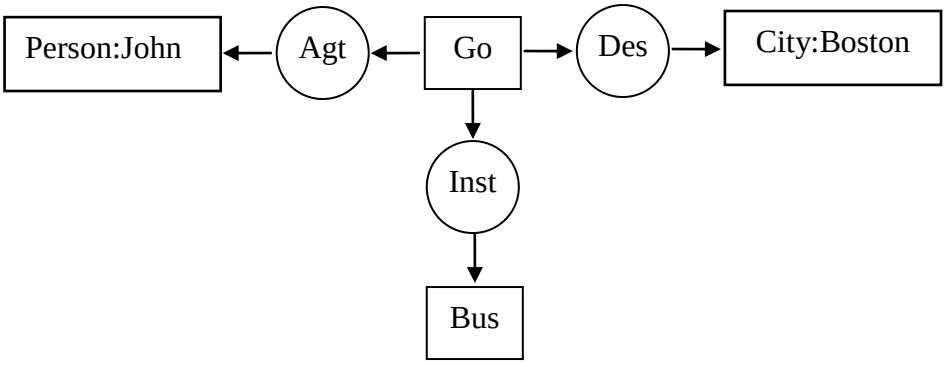


Figure 2-13: "John is going to Boston by bus", The square boxes indicate concepts and the circles indicate relations. Note that the concept Person has a referent "John" while the instantiation (referent) of the Bus is unknown.

In IBL and MIBL a primitive function can be defined to match this example. The primitive itself is "Go" and its parameters are Agent, Destination, and Instrument.

```
go ( Agent, Destination , Instrument )

Whereby the allowed word classes could be:
-  Agent of the word class Person
-  Destination of the word class City
-  Instrument of the word class vehicle
```

A concept always has a Type and can have a Referent. A referent is a particular object/concept. The Type must be based on ontology. (Ontology is a tree of types starting with the most general type at the top). A concept can either stand alone or be connected to a relation. It is not allowed to connect two relations directly with each other.

```
[Type: Referent] <-(Relation)-> [Type: Referent]
```

A single concept may be: `[Bus]` Which means "There is a bus".

```
[Proposition:
  [Woman: *x]->(Attr)->[Beautiful]
]
```

"There exists a woman x who is beautiful."

Language can be mapped into a conceptual representation using a conceptual parser. The conceptual representation is a representation of the dependency of the parsed text.

In this PhD project, conceptual graphs have been a useful representation to clarify the structure of sentences and to extract an ontology design of the domain. This clarification enables the system designer to map sentences into logic

2.6.3 Frame-based systems

Frame-based systems are knowledge representation systems that use frames. Frames combine domain knowledge in a structure for representing a stereotypical concept or a situation. A frame can have several kinds of information attached that describe the concept or situation further. The first to recognise the ongoing common trend in the 70s to represent knowledge in frames was Minsky (1975).

A Knowledge representation system that was inspired by Minsky's ideas is KRL (Bobrow and Winograd 1977). Goldstein and Roberts (1977) in turn were inspired by KRL when writing their frame-based system NUDGE. In their paper Goldstein calls the frames Frame Gestalts. The reference to "Gestalts" comes from the Wertheimers Theory of mind (Wertheimer 1923), that has fit in very well with frame-based systems.

Fikes and Kehler (1985) explored what is common in frame-based systems, quoted here:

- frames are organized in (tangled) hierarchies
- frames are composed out of slots (attributes) for which fillers (scalar values, references to other frames or procedures) have to be specified or computed
- properties (fillers, restriction on fillers, etc.) are inherited from superframes to subframes in the hierarchy according to some inheritance strategy.

This structures are remarkably similar to object oriented programming principles of C++ and Java. To some extend also SQL. Object oriented programming probably have roots in these systems.

Schank's Dependency Theory and causal chain, described in Chapter 2.4.4 earlier and in Schank (1975) is also a frame-based system.

2.6.4 Ontolological reasoning

Organised information is the key to deduction and reasoning. A list of nouns has no meaning unless the relationship between them is given. Aristotle was one of the first to

recognise the power of logic and organisation of information so it can be used for logic deduction (Aristotle, transl. 1989). A famous example of Syllogism, the logic that Aristotle defined, is:

"All men are mortal; Socrates is a man; therefore, Socrates is mortal."

A further advantage of organising information is the possibility to constrain the grammar to produce only rules that not only are grammatically correct, but also make sense. In section 6.2.2 the concept of word-classes has been introduced. As a reminder, word-classes are a group of words that belong semantically into the same category. For example the word-class "colour" has "blue, green, red..".

These word-classes are also used as primitive parameters. Section 6.2.3 on full corpus coverage shows in figure 6-2 how a corpus utterance that has become a grammar rule is extended with a word-class.

It is of advantage for consistence in reasoning and the search for information in the knowledge base, to combine all word-classes to a complete model that contains all concepts that the robot is dealing with in the domain. This model of word-classes is best organised in a hierarchical taxonomy, since a semantic category is often part of another more general category, sometimes referred to as superclass. Such taxonomy is conveniently represented by a tree.

Scientists have been studying on the structure of such taxonomies and their applications since the great philosophers Plato and his student Aristotle. These structures are often referred to as semantic networks or ontologies. The science of "ontology" is concerned with finding ways to structure taxonomies and how to apply these structures. Sowa, whose work has been briefly introduced in chapter 2.6.2, presented a "global" ontology which is at the top-level and every concept can be derived from it, see (Sowa 2005). His conceptual graphs are grounded in this ontology. It is the concern of ontology researchers to build top-level ontologies that capture very general concepts so they can be expanded to every possible domain. It is a philosophical question, how such a top-level ontology may be organised. From a Corpus Based Robotics point of view it is not necessary to cover more than what is found in the corpus, which simplifies the problem.

Ontologies guide the generalisation process for grammar and primitive parameters, the reflection of the ontology in the knowledge base gives the robot the ability to generalise concepts. For example it can infer that a "queen of spades" is a "card", or it can compare concepts with each other, when searching for suitable objects. See section 7.8 on problem solver, and specifically 7.8.4 on generalisation and references. This is important since referents in natural language are often underspecified, but referents have to be resolve within the rule frame.

One may wonder if existing ontologies could be utilised in an application. Unfortunately it is not a straight forward process to select the right meaning from existing ontologies, in the given context. For example, WordNet 3.0 (Miller 1985) defines a "card" in many ways, such as a calling card, a circuit board or and identity card. It is difficult for a system to reason with WordNet, since the class "card" has so many meanings in different contexts. WordNet also defines "playing card". WordNet attaches "suit" to "playing card", which is correct, but fails to connect "hearts", "spades", etc as semantic classes under "suit".

The created ontology becomes a world model of the robot. To create a complete world model, not only concepts (word-classes from section 6.2.2) are required. Also instances of objects are required. For example, Aristotle is an instance of a human. Furthermore he therefore "inherited" all the properties of humans, such as being mortal. In case of the MIBL projects, the robot has in his world model, an ontology of 3D objects, which can be manipulated. Further down these 3D objects are cards. Instances of cards are stored in the knowledge base.
What is in philosophy an ontology reminds a computer scientist of object-oriented programming. In fact, knowledge of physical objects and their properties are stored by the robot in an object-oriented format.

2.6.5 Newell and Simon General Problem Solver

Newell and Simon were the first to implement the idea of problem as a program. Their first program, the "Logic Theorist" was presented at the Dartmouth Summer Research Conference in 1955 (Newell and Simon 1956). Later an extended version, that separated

the problem definition from the solver was called GPS, the General Problem Solver (Newell and Simon 1972).

Typical problem solvers have need several critical steps: the definition of the problem space in terms of the goal to be achieved and the transformation rules. Simple problem solvers would use the means-end-analysis approach, to divide the overall goal into subgoals and attempt to solve each of those. Some of the basic solution rules include: transforming one object into another, reducing the difference between two objects, and applying an operator to an object. A table that specified what transformations were possible is required.

Given a robot that can specify its environment as states and actions on the environment as state transitions, a problem solver algorithm can be applied. A problem solver is a search algorithm that applies production rules (state transition rules) to manipulate a given state until a target state (goal) has been reached. The applied production rules can be stored as a solution path to the goal. Given that the robot knows the consequence of each action then state transition rules can be applied to its memory instead of carrying out the action immediately. Hence a problem solver is also a planner.

2.6.6 Lambda Calculus

The lambda calculus is a notation for mathematical expressions and functions. It was rediscovered as a versatile tool in computer science. The syntax of the computer language Lisp was inspired by the lambda calculus. The lambda notation requires operators, to be written before the parameters (prefix), like Polish notation.

For example expressions "x + 3" becomes "+ x 3", and "x^2" becomes "* x x".

LOGICAL OPERATORS OF THE LAMBDA CALCULUS

$\wedge$	conjunction (AND)
$\vee$	disjunction (OR)
$\neg$	negation (NOT)
$\Rightarrow$	implication
$\Leftrightarrow$	equivalence
Ξ	existential quantification
θ	universal quantification
$\approx$	equality

Table 2-1: logical operators in the lambda calculus

Functions:

The λ notes the function

$f(x) = 3x$ in lambda-calculus becomes $\lambda x.*3x$

The lambda calculus is used in natural language understanding to describe dependencies between words. A natural language expression, i.e. a sentence can be converted into a logical formula. Usually this starts with determining the parts of speech and using a syntactic parser. The resulting structure of noun (N), noun phrase (NP), verb phrase (VP), etc shows dependencies between the words. These dependencies can be expressed in a formal way with the lambda calculus. For instance consider

"John believes something is false"

Expressed in lambda calculus:

$\exists x(x \in L \wedge bel(John, x) \wedge false(x))$.

A translation can be defined from the lexical words, such as "believe" into the semantics "bel(y,x)". Like Discourse Representation Structures (DRS), the lambda calculus can represent dependencies and is an intermediate step. Lambda calculus expressions are logical and can be used for inference and reference resolution.

In order to learn and carry out instructions a robot must use inference or some form of mapping to extract the instruction from an expression in lambda calculus. For this process, background knowledge is required. This can be especially difficult for colloquial expressions, such as "what's up?".

3. Corpus Collection

Linguistic corpus collection is defined by acquiring and storing a corpus (Latin for body) of example dialogues usually by recording and transcribing or by gathering existing texts. In this chapter an experiment will be described where conversations between two people are collected to form the MIBL corpus. Corpora are not restricted to spoken and written text; they can include transcriptions of any interaction data, such as hand gestures, eye movements or a mouse cursor. Combinations of any of the listed modalities are collected in so called multi-modal corpora (Baldry and Thibault, 2006). Collecting a corpus is the first step when applying the corpus-based robotics approach. In order to create the corpus, the recordings are transcribed using the multi-modal transcription tool MuTra (described in section 3.4.1). The transcriptions include start time and duration of gesture and speech. The corpus provides a starting point to create a speech recognition grammar. The transcription process could be simplified by adding speech recognition software. However, all transcribed text has to be confirmed manually since the corpus provides the reference data for speech recognition and all further system development.

The corpus is to be analysed in order to design an agent that will be able to interact and perform actions that are found in the corpus.

3.1 The Instruction Domain

3.1.1 Experimental Constrains

With the experience and motivation from the previous project (IBL), criteria for the selection of a new application domain were determined. The criteria are aimed at investigating and extending IBL by applying scientific method[3].

i) The task must contain a wide range of instruction types.
(rules, sequences , repetitions). So they can be investigated.

ii) Ideally the task should be scalable from simple to complex. So a range of complexity can be investigated.

iii) The task should preferably have a small vocabulary (less than unique 1000 words). So the transcription and implementation is manageable.

iv) The task must be part of the natural environment of the instructor (user) so that instructor and student already posses the basic skills required.

v) The task should contain meaningful set of gestures / actions (multi-modal).

vi) The task should be unknown to the subjects beforehand, to set up a genuine teaching scenario.

vii) The domain size should be predictable. This can be achieved by measuring the rate of discovery of unique ways of expressing an instruction.

The constraints mentioned above, especially point *vi)* have to be determined by a pilot study. Furthermore a pilot study is a required step in the application of corpus-based robotics. A pilot study would require a corpus collection, transcription, search for language primitives and their types using 3-5 subjects.

Generally, there are many ways of expressing a verbal instruction, even in a restrained domain. Restrictions *iii)* and *vii)* are there to harness these restrains.

Given these constraints, game instruction seemed to be a good choice. In particular, card games come in a great variety of type and complexity, yet their vocabulary is restricted. All two player games listed in "the Oxford A-Z of Card Games" (Parlett, 2004), 23 different card games were investigated by counting the number of instructions in the form of a clause or sentence. It should be noted that the instructions from a professional book are more compact than verbal explanations of the same rule. As an

[3] The scientific method: hypothesis, experiment, observations, tests, confirmed theory

example, instruction sets from table 3-1 would count as one instructions each, per sentence. From the investigation, it was found that a typical card game has on average 38 instructions, with a std. deviation of 17.46.

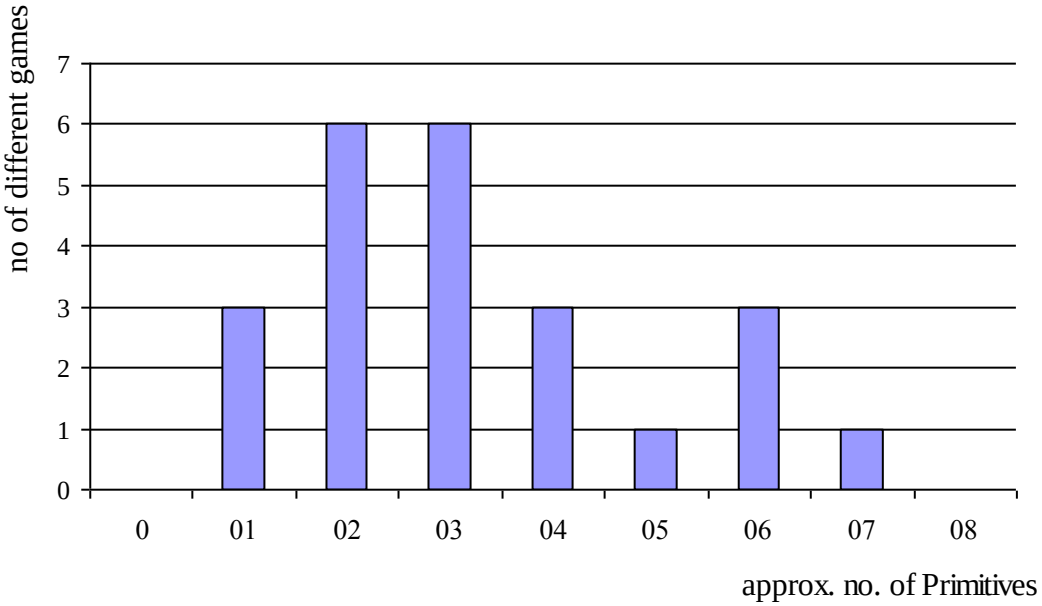


Figure 3-1: Game Primitives: A survey of 23 card games and their number of instructions presented as a frequency distribution showed that a typical game has an average of 38 instructions. See the list of games in Appendix A7.

In order to create a robot that would appear to be a reasonably intelligent card game player it was decided to choose a card game that has between 30 and 40 instructions.

3.1.2 Scopa

The Italian card game Scopa was chosen, since it had 35 instructions and is virtually unknown in the United Kingdom. That the card game is initially unknown is important as the investigation is about teaching. Yet all basic skills such as dealing a card or comparing cards are generally known to UK residents.

In Scopa, initially 4 cards a laid out face up on the table. Another 3 cards are dealt to each player. Scopa is a fishing-type card game (Parlett, 2004). A fishing game means that there are several cards face-up on the table, and the players have to match cards in their hand with the cards on the table. Matching cards on the table can be captured by the player in order to score. The game was originally played with a deck of traditional Italian cards. For the French deck (most common deck) the eight nine and tens have to be removed from the deck. Instead jack, queen and king are worth 8, 9 and 10 points respectively.

3.2 Procedure of Corpus Design and Corpus Collection

Multi-Modal corpora are still rare and contain very specific data; in particular there was no multi-modal card game corpus publicly available that would be suitable. As such we decided to setup an experiment to collect a multi-modal corpus.

3.2.1 Corpus Design

Corpus Design is concerned with decisions such as: how many subjects will be interviewed, what data will be recorded and how the data is formatted. Corpus Design decisions must be carefully considered with respect to the research that will be carried out with the resulting data. In a scenario where corpus-based robotics is applied, rather than researched, the domain is given initially. For example a company requires a vacuum-cleaning robot that can be naturally instructed. In the case of researching corpus-based robotics (specifically the MIBL project), the aim is to design the corpus to cover an as large as possible variety of features in the vocabulary and langue primitive types.

The corpus designer must consider that the collected data is stored in a format that can be used later for testing the performance of the developed system. Furthermore the data must be collected using the sensors on the robot, from the robots point of view. It is not advisable, for example, to use overhead cameras if the final robotic system will not have overhead cameras. A Wizard of Oz experiment is a proven way to collect a corpus. (Dahlbäck *et al*., 1993, Kyriacou 2004).

In a teacher student scenario, the teacher, who knows how to play Scopa, will explain the game to a student. After some practice the student can now become a teacher to explain the game to another student.

An informal pilot study has been carried out that consisted of 5 teaching sessions and their transcription of a very simple card game. It revealed that a teacher subject tends to use verb phrases and methods similar to those used when he/she was taught. In each dialogue the vocabulary and explanation techniques changed. Only some utterances of the dialogue were taught exactly like the teacher learned it. This led to the assumption that a longer teacher-student chain contributes to a larger variety in the corpus afterwards. Some teachers, however, may not come back to teach the game to another

subject, which would break the chain. To increase the chances of a longer chain a teacher was invited to teach two students in separate sessions. See figure 3-2.

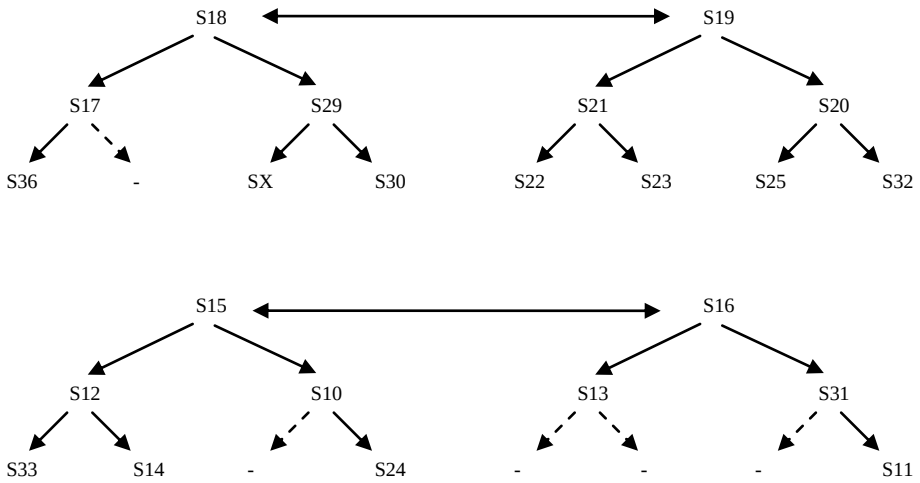


Figure 3-2: Tree of teaching dialogues. Two trees of this type were used to record dialogues. There are 6 dialogues in each tree, represented by the arrows and organized in three layers. Si is the subject number i. If one of the two subjects failed to attend, the chain was broken, here shown with a dashed dialogue line. These two trees are from now on refered to as data set-1 and data set-2.

It was also assumed that a longer break between learning and teaching the game reduced the similarity in the vocabulary used.

Initially two teachers had to be made familiar with the game. To avoid a bias as much as possible they were given two complete sets of written instructions of the game (Seed Set1 and Seed Set 2). Each instruction was written on a separate paper. The set was mixed so that the rules did not appear in a particular order. The two teachers studied the rules sets quietly for a few minutes. They re-ordered the sheets to help learning the game. Then they were invited to try to play the game and to clarify the set of rules by communicating with each other. This communication has been recorded with the experimental setup, but has not been used for any further analysis. Subject S18 was given Seed Set 2 and clarified rules with subject S19 who was given Seed Set 1. A further two teachers have been invited to do the same experiment whereby teacher S15 was given Seed Set 1 and subject S16 Seed Set 2.

Below is a list of instructions to the teachers.

INSTRUCTIONS TO THE TEACHERS

Instruction Seed Set **1**
Two players use a 40-card pack running A234567JQK in each suit.
Deal three cards each in ones, face down. And then four face up to the table.
When everyone has played their three cards, deal three more each from stock. Continue until all cards have been used and captured.
Each in turn must play a card from hand with a view to capturing one or more table cards.
Table cards may be captured by pairing or summing.
Pairing: An Ace takes an Ace, a Two a Two, and so on. Only one card may be paired in one turn, and if the hand-card can capture in either way it must do so by pairing.
Summing. A hand-card takes two or more table cards totalling the same as itself. For this purpose, cards count at face value from Ace 1 to Seven 7, followed by Jack 8, Queen 9, King 10. Thus a Seven will capture two or more cards totalling 7 (A+6, 2+2+3, etc).
When summing: Only one such combination may be made at a time
When you make a capture you place both the captured and the capturing cards in front of you and end your turn.
If you capture all the cards on the table, leaving none for the next player to take, it is a sweep. You indicate this by leaving the capturing card face down in your winnings pile, and will score 1 point for it at end of play.
You must play a capturing card if you can. If not, you must 'trail' by playing any card face up to the table and leaving it there. This is inevitable after a sweep.
When no cards remain in stock, the last player to make a capture (not necessarily the last to play, since he may be forced to trail) takes all the other table cards with it. This does not count as a sweep, even if, technically, it happens to be one.
Players sort through their won cards and score as follows: 1 point for taking the most cards. If tied, no one scores. 1 point for taking the most diamonds. If tied, no one scores. 1 point per sweep, as indicated by face-down cards.
The winner is the player with the highest score at the end

Table 3-1: Instructions to the teachers, Set 1

INSTRUCTIONS TO THE TEACHERS

Instruction Seed Set **2**
A 40-card pack is used. A234567JQK in each suit. The game is played with two players.
Deal three cards for each players hand. Don't show them to your opponent. After, deal four on to the table. (face up)
When players don't have any cards left in their hand, deal three more each from stock. The game ends when the stock has been used up and all cards have been captured.
Each player, in turn, plays a card from hand. The target is to capture one or more of the cards on the table.
There are two ways of capturing cards from the table: pairing and summing.
Pairing means a card in your hand pairs with a card on the table and you can take them to your stock. You must do pairing if you can.
Summing. A single card in your hand card can take multiple table cards which have as a sum the same value as the card in your hand. Cards count at face value from Ace 1 to Seven 7, followed by Jack 8, Queen 9, King 10. For example a six will capture two or more cards totalling 6 (A+5, 2+A+3, etc), and so on.
When summing: Only one hand-card can be used in one turn.
When you make a capture you place the involved cards in front of you onto your own pile.
If you capture all the cards on the table at once by summing, it is a sweep. You indicate this by leaving the capturing card face down in your winnings pile, and will score 1 point for it at end of play.
You must play a capturing card if you can. If not, you must put down any card face up anywhere onto the table and leave it there. Basically every player gets rid of one card every turn.

When no cards remain in stock, the last player to make a capture (not necessarily the last to play, since he may be forced to just add a card to the table from his hand) takes all the other table cards with it. This does not count as a sweep, even if, technically, it happens to be one.
After the game players sort through their won cards. Points can be scored as follows: 1 for taking the most cards. If tied, no one scores. 1 for taking the most diamonds. If tied,no one scores. 1 per sweep, as indicated by face-down cards in your pile.
The winner is the player with the highest score at the end

Table 3-2: Instructions to the teachers, Set 2

The invited subjects were mostly university students between the age of 20 – 30 years, only one female person. A significant number were not native English speakers. The pilot experiment and the final online experiments (chapter 8) had a similar distribution of age, gender and occupation.

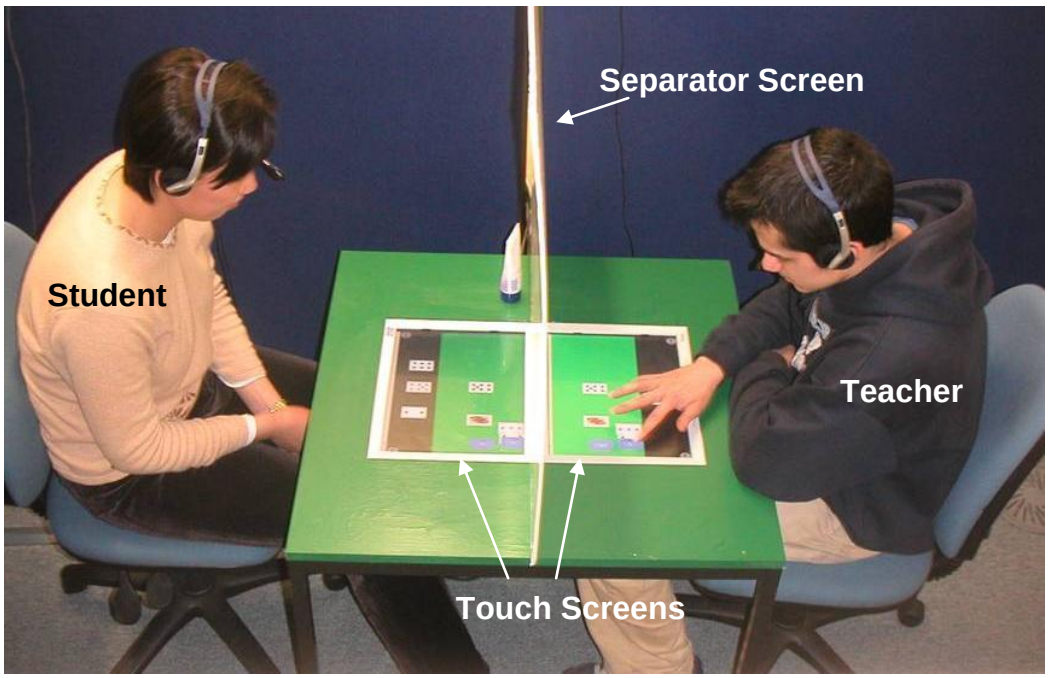


Figure 3-3: Experimental Setup for Corpus collection

The recordings if they are to be used later to test speech recognition must be of a good quality. The subject wore cost effective Plantronics headsets to improve the sound quality while recording. Each subject was recorded in uncompressed 16bit PCM WAVE Stereo format. Later experiments were carried out with an external Roland/Edirol USB soundcard to further reduce the signal to noise ratio.

3.2.2 Data Sets

DIVISION OF THE CORPUS INTO DATA SETS

Name	ID numbers of the experiment session
Data Set 1	03,06,07,10,11,12,14,19,20,21
Data Set 2	04,05,08,09,13,15,16,17,18

Table 3-3: Data sets of transcriptions

3.3 Multi-Modal Interface

3.3.1 A Robot with simulated Eyes and Arms

As argued in section 1.1, a truly natural unconstrained human-robot communication interface must be multi-modal. In future robots, multi-modal interfaces will require complex sensory processing, such as gesture and face recognition. As this project focuses on the problem of task learning, it was decided to devise a simplified interface that would still allow natural communication with human users, but simplify gesture recognition and robot actions.

The solution to the problem is to use a touch screen that allows at the same time to acquire human gesture information by the robot (without complex sensory processing) and execution of game moves (without complex actuators). The screen represents the world as the robot would see it through its vision system. The user is able to point at and manipulate objects on the screen as a demonstration of how to do the task. At the same time the user gives verbal instructions. Touch-screens have been used in multimodal human-robot interfaces for different applications, for example by (Perzanowski *et al.*, 2001), or for investigations in human communication (De Ruiter *et al.*, 2003).
A great advantage of using a screen representing the robot's world is that the robot can be simulated (a software agent), while the interaction and interface to the robot does not change. It also allows focusing research on human-robot interfaces without having to build a robot first.

Figure 3-4: A person is dragging a playing card on a touch screen. Gesture (Action) recognition through the touch screen is translated to movements of the card in the virtual 3D environment.

The robot is not embodied by an arm or face on the screen. The cards appear to move "magically" on the screen if the robot is acting. The robots voice can be heard through

the speakers. The same applies if two people interact, their voice can be heard but they can not see each other. If one moves a card it moves on the other screen as well.

A finished embodied robot could still have an attached touch screen mounted representing an Augmented Reality (AR).

3.3.2 Potential as Human-Computer Interaction interface

The investigation of human-robot instructions, in this project, is carried out with speech recognition and a touch screen interface. Essentially this reduces the human-robot interface to a human-computer interface. Human-computer interaction has a wider research and user community than human-robot interaction.
Touch screen interfaces are currently gaining popularity in the form of mobile phones, multi-media players and PDAs (Personal Digital Assistants).

3.3.3 Simlator Software

This section describes the simulator that simulates the environment and lets the users interact with it through multiple displays. The software developed to display the playing cards is based on the Qt (Trolltech®[4] 2005) and the OpenGL® API[2] and is platform independent. Qt is a cross-platform C++ GUI development library. OpenGL® is a standard for a 3D/2D cross-platform Graphics API. The playing cards are described as objects with parameters such as size, texture, position, orientation, static or movable. Therefore the system can be used not only for card games. The display software could display the image of any real world object. The user can manipulate these objects intuitively. The computers used for displaying the cards are linked to a server via TCP/IP. Performance is increased by having a computer for each Display Client due to the computational load for rendering the 3D environment. The server initially sends the display-clients the objects that need to be shown on the screen.

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[4] *Qt is a trademark of Trolltech in Norway and other countries.*
http://www.trolltech.com/

[2] *OpenGL® and the oval logo are trademarks or registered trademarks of Silicon Graphics, Inc. in the United States and/or other countries worldwide*.

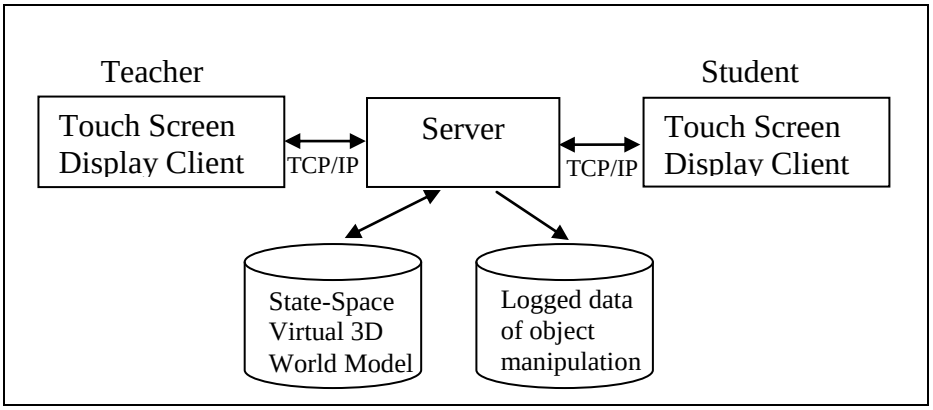


Figure 3-5: Corpus recording with two touch screens. If an object is manipulated in one screen it is also visible in the other, since the data is forwarded by the server. All data is logged and can be replayed for transcription.

All events of object manipulations are logged at the server (figure 3-5) and forwarded to all other connected clients. So if objects are moved on one screen, they move on the other screens as well. All events are also represented in a internal state-space world model (see section 3.3.4).

3.3.3.1 Interaction Control Protocol

A simple human-readable TCP/IP protocol called ICP (Interaction Control Protocol) has been created to communicate object creation and manipulation between server and client. Every packet is logged by the server into a human readable CSV (Comma Separated Value) file in the same format as it was sent or received by the server, with a time-stamp added in 10 Hz resolution. More than one event can be logged and forwarded within the 1/10 of a second time period; however the timestamp of these events would be the same. A 10 Hz sampling rate was found sufficient for the gesture recognition of this object manipulation task and has been used in related systems (Rybski. and Voyles, 1999; Davis and Shah, 1994; Oviatt *et al*., 1997). The 10 Hz timer for generating timestamps was synchronised with the real-time clock (RTC) of the server PC to maintain accuracy during long term recordings.

Initially the server accepts connections from the clients. In this implementation there are only two connections allowed, one teacher client and one student client. After the TCP/IP connection is established the client must report if it is a student or teacher terminal. The server will reply by sending the 3D world offset to place the client on the right side of the virtual table. After all connections are established the researcher will initiate the 3D objects (table and the cards) to be sent to the clients. Every 3D object is

assigned a unique ID at creation for referencing. Upon the first creation of the objects, the server software emitted an audible ring sound which can be used later to synchronise audio recordings with the timestamp of the gesture log file. The human-readable protocol format allows easy and transparent analysis of the communication system. Table 3-4 shows the protocol between server and display clients.

PROTOCOL BETWEEN SERVER AND DISPLAY CLIENTS

Name	Direction (C)lient to (S)erver	**Command,** Parameters Description
Ready	C→S	***R***, *ClientName* Client Reports that it is ready, followed by ClientName which is either "Teacher" or "Student"
Offset	S→C	***O***, *Offset_X, Offset_Y, GLWin_Width,GLWin_Height, Viewscale* Offset of the Camera in Global OpenGL coordinate frame
Move	C→S→C (forwarded)	***M***, *X, Y, UniqueID* Move the object with ID *UniqueID* to position *X,Y* in the OpenGL coordinate frame
Turn	C→S→C (forwarded)	***T***, *UniqueID* Turn object *UniqueID* 180 degrees around the Z-axis
Front	C→S→C (forwarded)	***F***, *UniqueID* Bring object *UniqueID* to the front of the OpenGL drawing list, which will make it appear in front of other objects.
Angle	S→C	***A***, *Theta_X, Theta_Y, Theta_Z, UniqueID* Set the object *UniqueID* rotation in all three axes, rotating about its local object centre. 0 degrees is in line with the global OpenGL coordinate frame.
Create	S→C	***C***, *X, Y, Size_X, Size_Y, isStatic, FileName, att1, att2, UniqueID* Create a card which is in effect a 3D OpenGL Box with a texture loaded from *FileName* and will be given the ID *UniqueID* from now on. (In this simplified version NonStatic objects are assumed to be playing cards and static objects are 3D Boxes which are push-buttons and the playing table)
Quit	C→S	***Q*** The client has quit the connection.

Table 3-4: Protocol between Server and Display Clients.

3.3.4 World Model for Simulator

As described above, every creation and manipulation of objects through the touch screen interface is recorded in a log file. To redraw the OpenGL world and give information about the objects, the state of the world and the information about the objects is saved in an internal representation (C++ Object CState). In order to use this world model in the transcription software, it is required to jump to any point in time of the recording, like on a tape recorder. This required the state-space of all world objects

at any point in time of the recording to be kept in memory. This approach is memory intensive but fast.

An object state holds:

PHYSICAL OBJECT IN THE WORLD MODEL OF THE SIMULATOR

Name	Description
UniqueID	its unique identifier for communication
Static	static or movable
Att	attributes, such as texture
x,y,z	world frame coordinates
xRot, yRot, zRot	Orientation relative to world frame
scale	scaling factor of
sizex, sizey	size of the object (default thickness is 4.0)

Table 3-5: Properties of the Physical Object in the World Model of the Simulator

As shown in figure 3-5, every communication is logged to a transcription file. Every state-space also contains a variable indicating the file position in the logfile (FilePos), the last action (Activity), the object ID of the object that was last involved in the action (ACT_ObjectID) and the number of objects in this state (NoOfObject).

The world model has no physics engine attached. This decision was taken since playing cards have a negligible mass. When an object is touched by the touch screen, it becomes the first object in the new state-space list so that it is drawn in front of the other objects. Any dragging move with the finger down on the screen will now immediately move the object that is under the mouse cursor relatively to the same position as the cursor / finger, to give an impression that one can drag objects around.

3.4 Multi-Modal Transcriptions

3.4.1 Transcription Tool

Recorded dialogues are transcribed to form a multi-modal corpus. A transcription has to capture the salient features of the gestures and utterances. Timing information has to be preserved in the transcription. The recorded audio, video and object manipulation data must each always carry timing information to allow a time-synchronised playback for the transcription. Similarly (Kvale *et al*., 2004) uses timestamps to synchronize inputs from touch screen and voice.

Annotation tools to create a corpus of multi-modal human-robot interaction have been used in related projects, such as the BITT Corpus for Topic tracking (Maas, and Wrede, 2006) or for instance "the Corpus-Viewer" of (Koide *et al*., 2004) , or the Home-tour scenario from (Green *et al*., 2006).

Transcriptions are commonly stored in Extensible Markup Language (XML), (Witt, 2002). The advantage of XML is the range of available parser and browsers that can be used to process the transcribed information. Existing multi-modal transcription and annotation tools such as ELAN, EXMARaLDA, TASX, MacVisTA consist of a Video playback window, a timeline window and an optional transcription window (Rohlfing K. *et al*., 2006). Most multi-modal transcription tools analyse video data. In corpus-based robotics, however, pre-processed sensor data, such as object coordinates can be available for transcription. This data must be imported into the transcription tool. In this research project the data is represented in a 3D environment on a screen rather than a video. Occasionally it is required to turn over a card, in order to check its ID for transcription. Converting the 3D environment recording into a video recording would remove the possibility to manipulate objects or change the camera viewpoint during transcription. Therefore a new transcription tool was designed called MuTra (Multi-Modal Transcription Tool). It was often necessary to go through menus and do several mouse clicks to transcribe a single utterance, since it is multi-modal; this was a further reason for creating a new tool. It is hard to develop a multi-modal transcription tool that suits all research projects due to the large variety of types of sensor data.

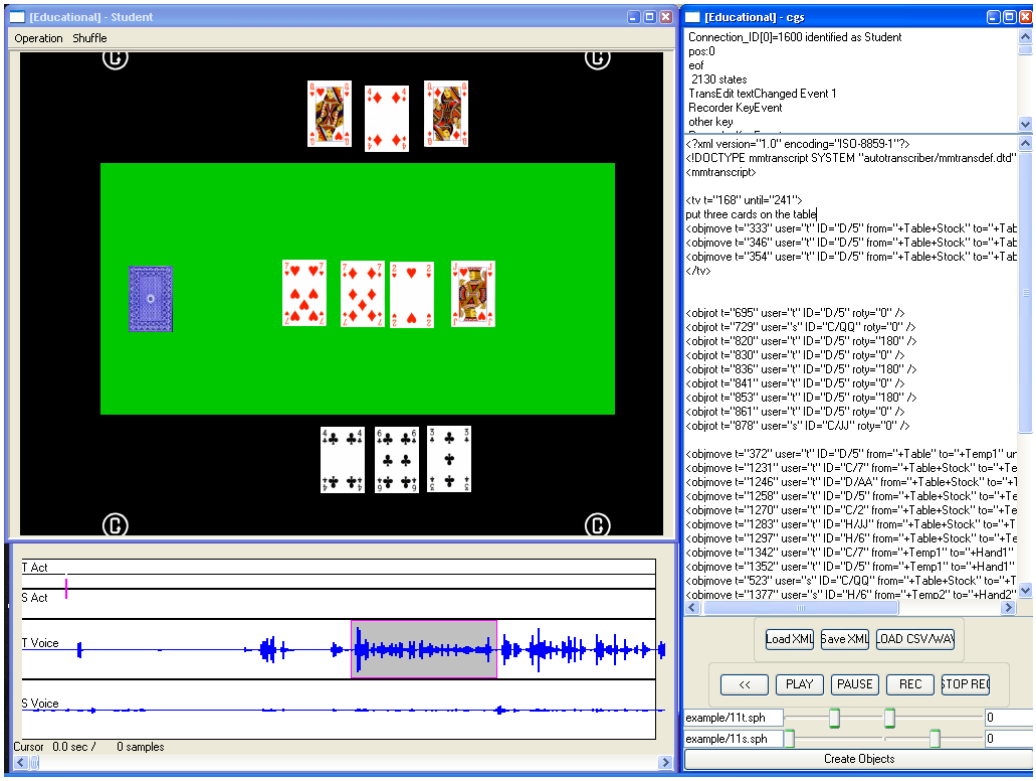


Figure 3-6: Mutli-Modal Transcription Tool MuTra, produced for transcribing the MIBL corpus.

3.4.2 XML Tags

There is no widely accepted standard for multimodal transcriptions. Most research groups create individual XML-tags to meet their needs. The wide range of data types in gesture annotation add to the diversity of XML-tags and the problem of standardisation. One could define, hypothetically, a XML tag for every action verb in English language. Bird and Liberman (1998), present a general specification body for multi-level annotations. The nesting of tags is limited in XML. It is not possible to represent partly overlapping events directly with partly overlapping XML tags.

The XML tags used for transcriptions are also defined in a DTD file (autotranscriber/mmtransdef.dtd) which can be used by tools such as Expat to check the syntax of the XML transcriptions. DTD (Document Type Definition) files contain a definition of XML tags and their syntax.

Example	Description
<mmtranscript> … </mmtranscript>	root tag, indicating a multi-modal transcription
<objmove t="315" user="s" ID="D/7" from="+Table+Stock" to="+Table" until="327"> </objmove>	linear movement of an object ***ID*** by ***user*** at time ***t*** from location ***from*** to location ***to*** ending at time ***until***. Whereby from and to are a semantic label of an area. If areas overlap they are concatenated with +.
<objrot t="388" user="s" ID="D/3" roty="0" /> </objrot>	The ***user*** rotates object ***ID*** at time ***t*** around the y-axis to ***roty*** degrees. (the duration of the rotation is assumed to be 0.1 second if the ***until*** parameter is not given)
<tv t="2396" until="2428"> text </tv>	An utterance with the teachers voice (tv) starting at ***t*** lasting until ***until***. The transcription text of the utterance follows before the closing tag </tv>
<sv t="2424" until="2426"> text </sv>	An utterance with the students voice (sv) starting at ***t*** lasting until ***until***. The transcription text of the utterance follows before the closing tag </tv>
<corrected> text </corrected>	The text enclosed in this tag will be filtered out when the transcription is used to build grammar. The transcriber has here the opportunity to remove repeated words and hesitations. In some cases also unfinished utterances, where the speaker changed his mind in the middle of the utterance.

Semantic Annotation Tags
(domain dependent)

<dealing>… </dealing>	Indicates the dealing phase of the game
<game>… </game>	Indicates the playing phase of the game (after dealing)
<counting> </counting>	indicates the game phase of counting the points after the outplay has finished
<pairrule phase=example no=1> </pairrule>	indicates the description of the pairing rule
<sumrule> 	indicates the description of the summing rule
<value> </value>	indicates the description of the value of cards
<exist> </exist>	indicates utterances that describe which cards have or have not been taken out from the deck (exist-rule)

Table 3-6: Transcription Tags. All timestamps in the transcriptions are given in 1/10 of a second. For example t=315 means 31.5 seconds.

3.4.3 Transcription Method Guideline

In order to reproduce the method of transcription the guideline is described here, part of the transcription for the MIBL corpus was done by a specially hired person. Each utterance is transcribed. If an utterance contains several instructions they may be transcribed separately. Hesitations are transcribed and marked with <hesitation></hesitation>. If a sentence was incomplete, aborted or corrected by the speaker, the <corrected> - XML tag is used to remove text so that a sentence is left over that makes sense. The transcriber must strictly follow the audio data. It is not allowed to invent and add words to complete a sentence. The teacher is transcribed with <tv> tags and the students voice with <sv>. Audio is marked first, which creates these tags with accurate timing information. The timing information must be accurate enough so that it can be used to cut the audio file of the whole session into utterances. Any gestures that belong to the utterance must be put inside the <tv> tag. If more than one gesture belongs to the utterance, they are all put inside the <tv>. These gestures are regarded as a gesture group. The conversation has to be transcribed from the start when the use of the touch screen was explained until the end of the first test game.

3.5 Initial Corpus analysis

3.5.1 Quantitative

The MIBL corpus has 21 recordings. The first two recordings are between the 4 initial teachers, done while they were clarifying the rules. They have not been transcribed and analysed. The two pairs of initial teachers discussed the written rules to clarify between themselves. This minimised the possibility of unnaturally influencing the subjects by the experiment designer. There would otherwise be a danger of the experiment designer to express sentences and rules with the robotic reasoning in mind. This leaves 19 teacher-student recordings which have been transcribed. After transcription, some initial figures on the size of the corpus can be made:

The MIBL corpus has 35322 words in total. That is approximately the size of this thesis. Of these words, there are 1136 distinct words. The most common words, sorted by frequency are “the”, ”you”, ”and”, ”so”, ”ok”, ”a”, ”I”, “cards”, ”yeh”, ”to”, ”that”, ”of”, ”one”, ”er”, ”card”. Figure 3-7 shows their frequency and Appendix A1 lists all distinct words in the corpus and their frequency. In comparison the IBL corpus had 6600 words and 330 distinct words. Working with a corpus, that has to be manually transcribed and analysed, can be a mammoth task. Every decision that requires going through the transcription again has to be carefully considered, since it is time consuming. To go through the MIBL corpus to annotate a particular occurrence, such as a reoccurring action, in the text takes approximately 20 man-hours.

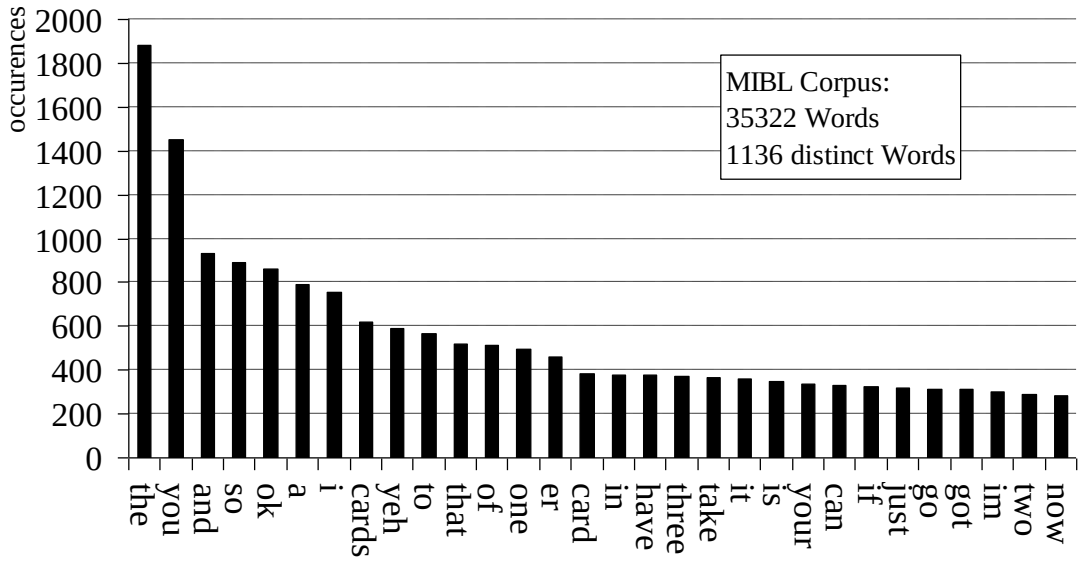


Figure 3-7: Word Frequency of the 30 most common words in the MIBL corpus

3.5.2 Types of Instruction Primitives

Analysing the utterances of the transcriptions reveals primitive procedures which the robot has to be able to carry out before learning from the end-user can start (the robot's "prior knowledge"). Such "language primitives" are specific to the level at which humans communicate with each other. They can constitute complex robot procedures in the background. These language primitives can be categorized into:

facts , sequential actions , context indicators , conditionals

Some examples of transcriptions and corresponding primitives are shown here:

TRANSCRIPTION WITH PRIMITIVE

Type	Utterance transcription	Primitive
facts	21.xml/696-723: "erm ok so the deck were playing with" 21.xml/729-748: "is a forty card deck" 21.xml/758-779: "with the eights nines and tens **removed**	not_exist(cardname=08, cardname=09, cardname=10)
sequential actions	03.xml/2431-2481: "er what you do first of all is… er you **deal** three cards for yourself face down"	move(cardname=cards, num_of_cards=3, source=?, target=hand2)
context indicator	11.xml/1588-1619: "and er this is how the game goes um"	context(indicator=new_case)
context indicator + conditional	07.xml/1167-1188: so if i **had** a four in my hand	context_type(type=imaginary) ifloc(cardname=a-four, num_of_cards=1, location=+hand1)
conditional	06.xml/-: " so if **youve** got a two in your black area"	ifloc(cardname=a-02, num_of_cards=1, location=hand2)
conditional	17.xml/1434-1507: " i could **capture** a card in the middle by **getting** another jack and then..."	ifloc (cardname=a-card, num_of_card=1, location=+table (ifcond (cond.type=equal, comparison=value, lhs =a-card, rhs1=jack, rhs2=?)

Table 3-7: Examples of transcriptions and their primitives and primitive types. Verbs that help to identify the primitives are marked in bold font.

As for context indicator and conditionals, examining the corpus for game rules reveals that a game rule is constructed from:

1. initial *context indicator*: e.g. “suppose you” or “if”
2. *conditionals*: e.g. “have an ace” or “cards with equal rank”
3. a sequence of *instructions* that have to be carried out when the conditionals are satisfied

These primitives are inserted into the transcriptions as XML tags manually. The question mark in the semantics (table 3-7) means, that there is missing information. Missing information is completed by combining semantics, multi-modal integration and by requests to the teacher. See sections 6.2.4, 7.5, 7.6 for detailed description on missing information.

SAMPLE OF IDENTIFIED LANGUAGE PRIMITIVES

Type	D/P	Language Primitive
fact	D	value(cardname, value)
fact	D	exist(cardname) / not_exist (cardname)
conditional	D	ifcond(how, what, lhs, rhs, rhs,…)
conditional	D	ifloc(cardname, location)
conditional	P	until(...)
context	D	new_case()
context	D	type(imaginary / real)
action	P	move(cardname, amount, from, to)
action	P	turn(cardname)

Table 3-8: listing of some primitive functions found in the MIBL corpus.
D=Declarative primitive, P=Procedural primitive. For a complete list of primitives see Table 3-9

In the case of action-primitives (require the robot to do physical action), the verb is often a synonym to the primitive name itself. Facts, such as `exist, value` contain a form of “to be”. Conditional primitives can always be rephrased to start with “if”. Since “if” is not always used, they are not as easy to identify as other primitive types.

3.5.3 List of Language Primitives

COMPLETE LIST OF LANGUAGE PRIMITIVES

Name	parameters	Description
context	*new_case*	a context change that will trigger a new rule-frame to be created
context_type	*imaginary*	the situation that the teacher describes is imaginary
context_type	*real*	the situation that the teacher describes is real (objects and actions exist in front of the robot)
sequencetrigger	*explain*	a initial sentence saying that the teacher will explain the rule, this is required for multi-modal integration.
players	*n*	Number of players in the game
imitate	*now*	request or implicit request to imitate the teachers action or follow a verbal command immediately
loopinicator	*each*	meaning that the action has to be repeated for each player
clause_relation	Prim,Prim,*modify*	modify last clause with this clause
clause_relation	Prim,Param,*query*	Teacher asks a question, the primitive is modified to become a question
clause_relation	Prim,*ns*,*not*	Negate, not true, make primitive negative
query		User asks question to the robot
move	CardCatNP,Loc,Loc	moving cards from Loc to Loc
move (pointing)	CardCatNP,Loc,Loc	pointing: whereby source and target location are the same Loc
turn		turn cards over
value	CardCat , Value	describes the value of a card in points
not_exist	CardCat	cards that have been taken out from the game/stockpile
exist	CardCat	cards that exist in the game
ifloc	CardCatNP,Loc	introduction of a card that is at a specified location
ifcond	Type,Property,LHS, RHS1,RHS2...	comparison of objects (cards) Type is the type of comparison i.e. “equal”,”smaller”.. , Property is “colour”,”rank”,”value”. LHS=objects on Left hand side of comparison, RHSx = right hand side
Dialogue Manager (dm)		
dm*(game_one)*	*game_one*	Dialogue move to switch from greeting the user to learning a specific game
dm*(ok)*	*ok*	positive confirmation “yes” , “okay”...
dm*(wants_play)*	*wants_play*	user wants to play with the robot, switches from greeting or learning to a playing state
dm*(shuffle)*	*shuffle*	will trigger the robot primitive on shuffling the deck
dm*(exit)*	*exit*	end of the dialogue
dm*(start_again)*	*start_again*	triggers the knowledge base to be erased and the teacher can start from the beginning
dm*(clever)*	*clever*	to deal with impolite expressions from the user
dm*(erase)*	*erase*	“forget that”, “erase that” or similar expressions will trigger a deletion of the most recent rule-frame instruction
dm*(pardon)*	*pardon*	user did not understand what the robot said, which will trigger a repeat
dm*(robot)*	*robot*	user wants the robots attention by saying its name
dm*(turn-human)*	*turn-human*	“its your turn” or similar expressions will trigger this
dm*(turn-robot)*	*turn-robot*	“its my turn” or similar expressions will trigger this
dm*(dummy)*	*dummy*	dummy event required for implementation
reply		Reply to a question from the Dialogue Manager

Table 3-9: List of language primitives and their description. CardCatNP consists of a noun phrase that can include the number of items refered to and optionally a location, for example “the three cards here”. This list shows not only the primitives from the initial analysis, it is a complete list.

Shown in the table above is a list of language primitives that have been analysed and implemented from the corpus. At the initial corpus analysis the primitives will not be as clear as described above to the eyes of the developer. Primitives can be formed as the developer looks for similarities and tags them with XML while keeping notes on possible primitives.

There are only 3 action primitives that were dominant during the dealing and game phase: moving, turning and pointing. At the end of the game, the cards are counted, which would be another action primitive, however this phase was not analysed in this work. A further possible action primitive could be visual-attention, which was not implemented since the robot is always looking at the card table and has a mental image of all the cards locations. The dialogue structure is expected to be different between human and robot therefore the dm-primitives (Dialogue Manager) are not completely created from corpus analysis. dm(erase), dm(pardon) and dm(robot) come from the experience with dialogues in IBL.

4. Action and Gesture Recognition

The term “gesture” has no commonly accepted definition. The Oxford Advanced Learner’s dictionary (Hornby, 2000) defines gesture as “a movement that you make with your hands, your head or your face to show a particular meaning”. In general terms, gesture could be defined as the act of non-verbal communication using body parts. An action could be defined, for example, as manipulation of objects. Demonstrating an action to another person or robot is also an act of non-verbal communication using body parts. Cadoz (1994) laid out three major *functions for gesture*:

- **semiotic**: it is used to communicate meaningful information; (for example sign language, pointing)
- **ergotic**: it is used to perform manipulation in the real world; (manipulating, creating of objects, for example cooking)
- **epistemic**: it is used in learning from the environment through tactile experience (by touching and manipulating objects).

The *functions of gesture* may be augmented by using an instrument according to Coutaz and Crowley (1995) .

In this respect gesture recognition systems link gesture and action and can be treated the same from a computation point of view as well. Therefore there is no differentiation between the terms “action” and “gesture” in this chapter.

The MIBL corpus contains some semiotic gestures while the majority is ergotic. Epistemic data can be found in the recordings where the teacher initially explained how the touch screen works. This epistemic data has not been used for this research. In card games, gestures can be pointing gestures, gestures moving cards from one place to another, e.g. stack to table, hand to table, re-arranging gestures, making a group of cards look tidier and turning over gestures.

4.1 Gesture Recognition by spatial mapping

Action and gesture recognition is in essence like speech recognition, where analogue sensor data streams are mapped into categories. These categories are more meaningful for further interpretation and reasoning. Commonly, machine learning algorithms such as Hidden Markov-Models (HMM) or neural networks are applied for this task. In some cases simple thresholding algorithms are sufficient.

The MIBL system uses a touch screen to simplify gesture recognition. The touch screen operates as an additional mouse to a computer. The effect of a user touching the screen is signalled as a mouse button-down event in the operating system. The MIBL GUI-Client translates these events to a "touch" of a virtual object. Moving cards on the touch screen is intuitively done by touching the card and dragging it to another position. The resulting data is a trail of X, Y coordinates of where the card is going. In case of a real service robot, this tracking data of cards on the screen could be the output to the service robot's vision system.

The X,Y data of the moving card must be categorised to complete the gesture recognition. The starting position, where the card was first touched (Figure 4-1) is compared to area boundaries which have been predefined (Figure 4-2). Combined with the type of action and object ID, this provides the initial parts of the gesture primitive:

For example:

<objmove t="2416" user="t" ID="D/5" from="+Table+Stock" to=? until=? ></objmove>

The target position "to" and end-time "until" is still unknown at this point. An algorithm continues to collect X,Y data of the manipulated card until the card comes to a rest or another card was touched. The final X,Y position is then categorised again by comparison to predefined areas. The gesture primitive is now complete.

<objmove t="2416" user="t" ID="D/5" from="+Table+Stock" to="+Temp2" until="2442"></objmove>

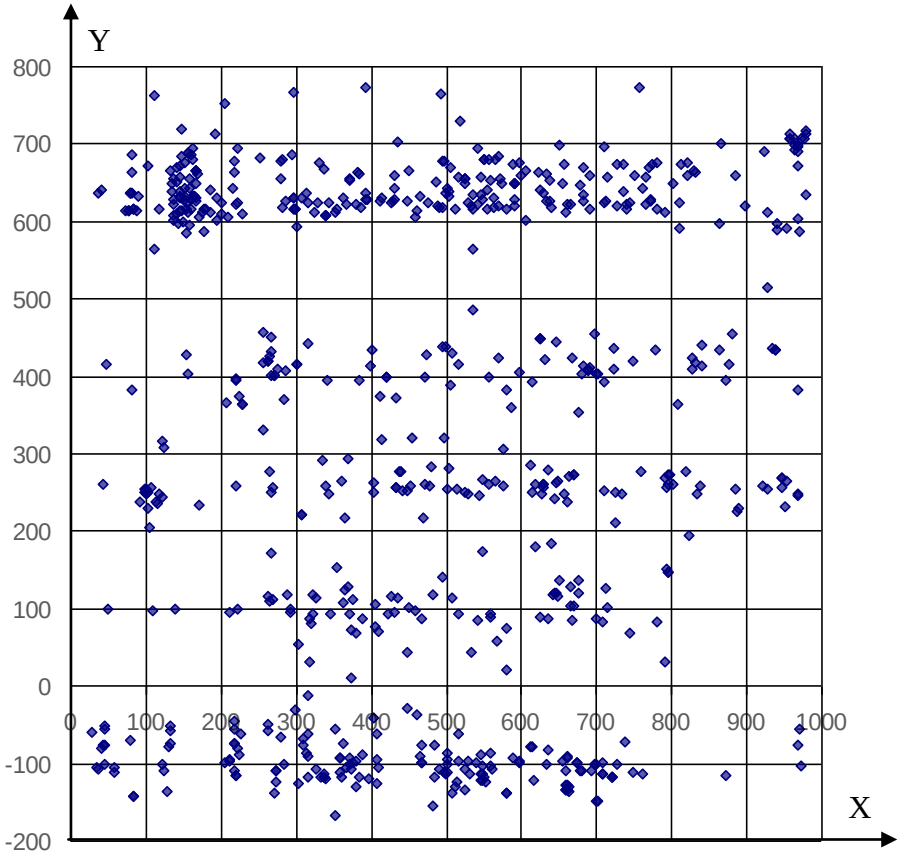


Figure 4-1: Resting Positions of Cards. Area map of the card game virtual area. Each dot indicates a resting position of a card during dialogue session 03.xml. The card positions concentrate clearly along 5 horizontal lines. These lines are labelled "hand2" (student's side), "temp2", "table", "temp1", "hand1" (teacher's side). Furthermore a concentration around 150,650 indicates the winning pile "side2" (see Figure 4.2)

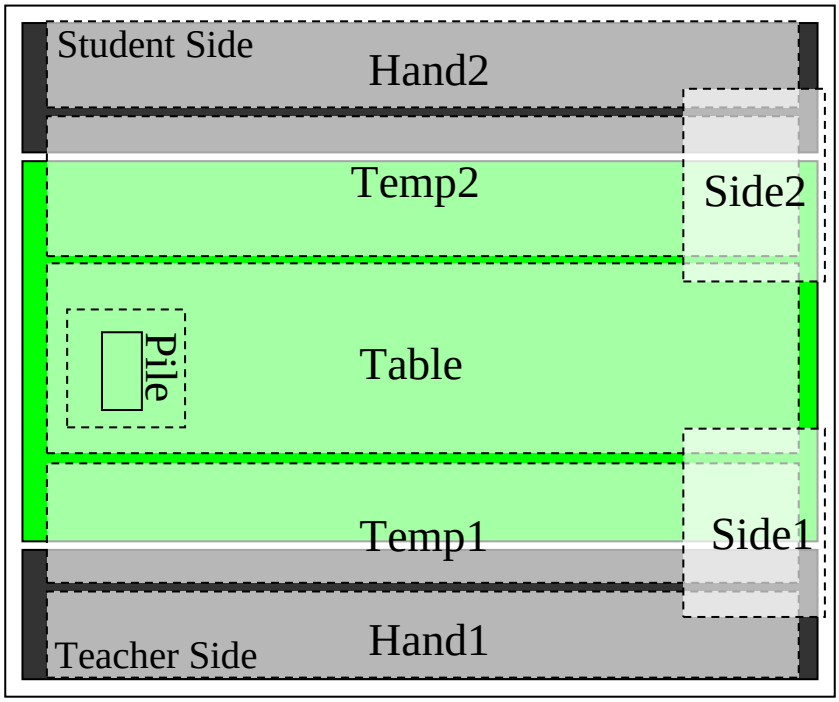


Figure 4-2: Area definition. After observing the actions of the users in the corpus, areas have been defined on the touch screen. Temp1 and Hand1 are on the teacher's side. Temp2 and Hand2 are on the student's side. The teacher and the student can only see and manipulate cards in their hand area and on the table.

Gesture recognition is a skill set, as mentioned in Section 2.1, skills can be learned but that is not the aim of this work. Therefore the gesture recognition skills are pre-programmed as a categorisation algorithm.

Gestures are recorded in a transcription file in XML format including time of start and end of movement, player doing the move, card identity and start position and destination, such as for instance:

<objmove t="2416" user="t" ID="D/5" from="+Table+Stock" to="+Temp2"
until="2442"></objmove>

Move-gestures that have the same start and final position category are often pointing gestures, or local rearrangements (tidying) of cards. In some card games or other domains, spatial relations are important. At this point an algorithm would have to be included that can recognise relative positions such as “A left-of B” or “A on-top-of B”. In the game Scopa, which was investigated here, relative relations however, were not of importance.

The gesture recognition process is used in the MIBL robot module called autotranscriber (Wolf 2008, MIBL Manual). The gesture recognition process can also be used to assist multi-modal transcriptions. Once the initial area categories have been determined, gesture recognition is automatic. A smart transcription tool that could be trained while transcription is going on and suggest gesture transcriptions to the user is of advantage, since the transcription process is tedious. At the stage where utterances are transcribed, it is useful to have gestures already transcribed/recognised to indicate any connection between gestures and utterances in the transcription. This provides reference data for multi-modal integration algorithms.

GESTURE PRIMITIVES

Gesture Primitive	Description
`move(object,from,to)`	Moving an object. Whereby `object` is a physical object and `from / to` are locations from figure 4-2
`move(object,loc,loc)`	Pointing at an object. Whereby `object` is a physical object and `loc / loc` are the same, since the card is only moving very slightly when touching it for pointing at it. locations are from figure 4-2
`turn(object,side)`	Turning an object. Whereby `object` is a physical object that is rotated around its Y axis. `side` “`up`” is defined as 0° and “`down`” as 180°

Table 4-1: Table of Gesture Primitives in the Corpus

Occasionally pointing gestures are also found in the corpus. The teacher wiggles a card. This can be recognised as a special case of moving, whereby from and to locations stay the same. Furthermore cards are sometimes rearranged to look tidy. This can be falsely recognised as pointing.

The screen should have enough space for all objects to spread out. In a too small setup, humans will otherwise start rearranging objects because there is not enough space, which makes gesture recognition unnecessarily complex. Unfortunately, the MIBL corpus is affected by rearrangement gestures, especially when the game progresses many cards clutter the screen.

4.2 Gesture Production

Following the corpus-based approach, every gesture primitive is not only recognised, but can also be performed by the robot. The robots planner produces low-level robot instructions (LRI) (Chapter 7.8.6) which have the same level and syntax as the primitives. While the robot carries out its actions (move / turn), the robot sees the consequences with its vision system. Even though in the MIBL example this is going on a touch screen, there is still the separation between the LRI-module which generates the gesture and manipulates the object and on the other side the autotranscriber-module, "the robots eyes" which recognises its own actions. This feedback loop gives the robot the opportunity to recognise a failure of its actions. For example if the teacher interferes with the process.

4.3 Advanced Gesture Recognition

Statistical learning algorithms could be used instead in a real service robot, if the vision system output coordinates are noisy or if there are no clear cut boundaries. In these experiments it was found that a statistical categorization is not required because of the clear separation shown in figure 4-1. In other cards games however, the situation can be more complicated. It is advised to display histograms of start and end points of manipulators in order to determine the predefined areas. These boundaries of these areas could be defined by the density of the resting positions, based on data such as in figure 4-1. The separation into areas could further be defined with Voronoi diagrams. A Voronoi diagram is a set of points equidistant to two or more obstacles in configuration space (Russell and Norvig 2003)

This work deliberately used a simplified method for gesture recognition in order to concentrate the research on higher level reasoning. The simplified method could be summaries by using predefined Areas, and if a card has moved to that area a gesture is recognised.

With real robots, proper gesture recognition systems and skill learning systems would be needed. The research field of imitation learning and human motion recognition provides systems for this purpose. These proper systems could "plug-in" to MIBL. For instance Roy (2005) analogue beliefs and the categorizers, reviewed in chapter 2.6.1. Alternatively the HAMMER framework (Demiris and Khadhouri, 2005) that can learn from observing the demonstrator. The advantage of the HAMMER architecture is that actions can be recognised (perceived) and reproduced within the same architecture. Another system that can do human motion recognition specifically aimed at categorising these actions into sequences is from (Loesch *et al.*, 2008, Otero *et al.*, 2006). It uses a body model of a human to match tracked motion data against the model. All three mentioned systems are designed specifically for human-robot interaction.

5. Integrating Gesture and Language

5.1 Challenges of Multi-Modal Integration

As established in the introductory section 1.1, natural communication between a human and a robot requires a multi-modal interface. Typically the modalities of speech and gesture are used to achieve natural communication going beyond the traditional input modalities of keyboard and mouse. The subject of multi-modal integration has its origins in Human-Computer Interaction (HCI), see for example Bolt (1980), but has become more and more important in Human-Robot Interaction (HRI) probably due to the fact that robots are embodied agents. On a first encounter of a non-expert user, speech, touch and gesture will be the first modalities of interaction, especially if a keyboard or screen is absent. With multi-modality comes the problem of multi-modal integration. The subject of multi-modal integration is concerned with combining data from modalities into a coherent form so that an interpretation is possible. Multi-modal integration is taking advantage of the additional information available, compared to a single modality, by removing redundancy and minimising ambiguity and resolving references such as pronouns. Redundancy in the information channels can be taken advantage of in multi-modal integration for the purpose of synchronisation and increased confidence. Fig 5-1 shows a simple block diagram of information flow in human to robot instruction which illustrates the "communication channels" and the common knowledge connecting the teacher and student.

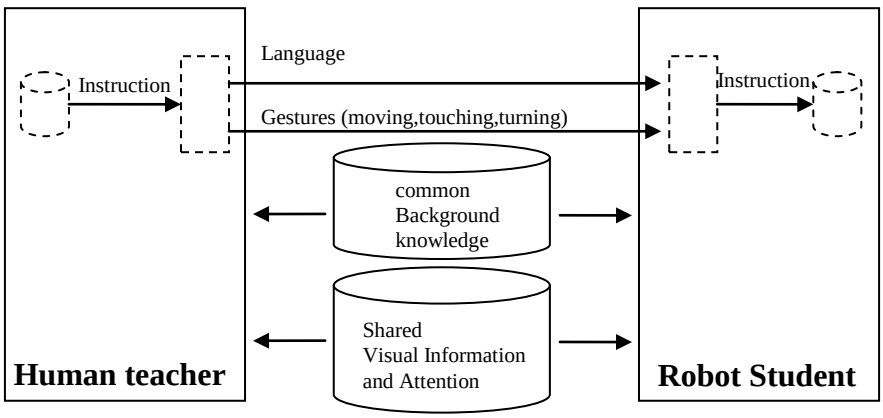


Figure 5-1: Information exchange: Instructions from a human teacher to a human student or robotic student are divided between two communication channels. Both share common background knowledge about the domain. Teacher and Student are both looking at the task with their eyes and share visual information, .i.e. the existence and position of objects in space.

Instructions are explicitly exchanged by communicating in the obvious modalities of gesture and language. However, often these instructions are underspecified. To complete the missing information it is often required to draw on visual information, background knowledge and discourse. While the integration is described in this chapter, the completion process using background knowledge and discourse is described in chapter 7.

5.1.1 The Timing Problem

From a robot perspective the modalities are two communication channels that need to be recombined into one message. This problem appears to be related to the time-synchronization problem in communication engineering. Another related engineering discipline is multi-sensor fusion, which is often solved by using Kalman filters (Maybeck 1979). However, the integration of free flowing speech and gesture has added complexity.

The timing problem can be brought down to the fact that confusion arises about which utterance has to be linked to which gesture, because they are not strictly synchronised. Figure 5-2 shows an example of relative timing of speech and gesture from the collected corpus of card-game instructions. In, addition it will be shown that, in free flowing conditions, timing does not provide sufficient information for correct multi-modal integration, which needs to rely also on semantic criteria. Therefore the term "pairing" is used rather than the term "time-synchronization".

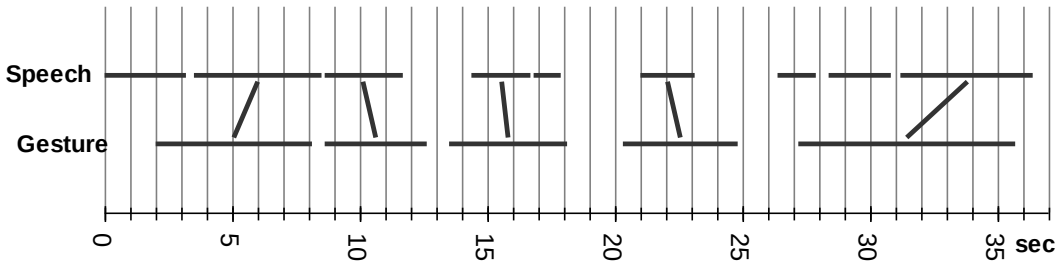


Figure 5-2: Time-lines of speech and gesture, where diagonal lines indicate which utterance and gesture are paired together.

This example of the corpus confirms that utterances can follow up very closely behind each other, this was also observed by (Oviatt 2001) who writes: "*It is a myth that speech and gesture always have time overlap if they belong together."*

From a human perspective, the problem of multi-modal pairing can be referred to as "acoustic packaging" of actions using language. Brand and Tapscott (2007) investigated infant directed speech. They found that infants can segment a flow of actions into segments of actions by the help of speech from the age of 9.5 month. Segmentation is part of recognising an action and its intention. It is suggested that infants in their early live use intonation and speech to mark the beginning or end of an action. These actions can be novel to the infant. This speech acts coincide in timing with the action. Later on in live as the "acoustic packaging" has been bootstrapped (bottom up), the exact coincidence between speech and action becomes less important since the actions are not novel anymore and can be segmented by recognition.

5.1.2 Pairing and Unification Problem

As discussed in the review of multi-modal human-robot interaction systems (section 2.3.3), the integration problem has also been addressed in the past by Oviat (1999); Johansson (2001); Nigay and Coutaz (1995); Chai (2003), where it is sometimes referred to as multi-modal fusion see Djenidi *et al*., (2004).

In this thesis a late fusion model is described that can successfully select (pairing) language utterances and gestures and combine (unify) the information stored in both to a single representation of a primitive. A simplified block diagram of the process is shown in figure 5-3.

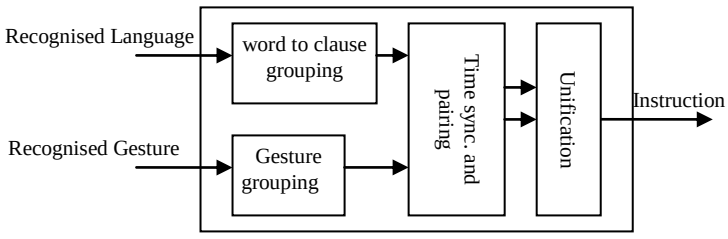


Figure 5-3: Multi-modal integration system

Figure 5-3 is clearly different from an early fusion model, such as Roy (2005), where fusion would happen already at the recognition phase.

In order to integrate multi-modal information, the data types that overlap need to have a coherent format. Furthermore a decision needs to be taken on how the overlapping information can be unified into a single data set. The coherent representation and unification steps are described in section 7.6 after language semantics and pairing have been introduced in this chapter.

5.2 Multi Modal Data Characteristics

5.2.1 Distribution of Information in Multi-Modal Data

Within one dialogue there can be a different distribution of information between the two modalities. Table 5-1 shows examples of the MIBL card-game corpus. The first of these examples (06.xml) is a uni-modal instruction using only speech. The second example is a multi-modal instruction, compiled of both speech and action on cards.

```
06.xml:
<tv t="1092" until="1141">
  the idea is to win the most cards from the middle until your hand goes
</tv>

07.xml:
<tv t="949" until="995">
  and if you flip these three cards they are your hand
  <objrot t="954" user="t" ID="C/KK" roty="0"/>
  <objrot t="960" user="t" ID="D/2" roty="0"/>
  <objrot t="966" user="t" ID="C/7" roty="0"/>
</tv>
```

Table 5-1: Examples from the card game corpus.
`t` and `until` represent the time of start and end of the event.

In the extreme, one might see cases where multi-modal instructions only include action-demonstrations, e.g. “to deal cards you do as follows”, followed by a long sequence of actions. This would correspond to the extreme left end of the diagram in figure 5-4.

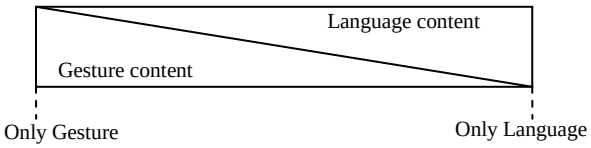


Figure 5-4: Spectrum of information content divided between gesture and language in a conversation

In general, a multi-modal instruction unit is composed of an utterance associated with a sequence of actions of variable length. In the MIBL corpus there were no instructions that were purely described by gesture. Utterances themselves are sequences of words that are grouped through the setting of timeout limits in the speech recognition engine. In the following section, the method used for the grouping of actions (gestures) is

described. The method has been developed by investigating the dealing-phase of the corpus of game instructions.

5.2.2 Gesture Groups

One instruction utterance can be accompanied by several gestural instructions. For instance, “deal three cards onto the table” entails 3 card displacement actions. Or in an example of another domain: “use two spoon of coffee per cup” entails a repetition of elementary actions. Thus, single actions need to be grouped into a unit that complements the single spoken clause.

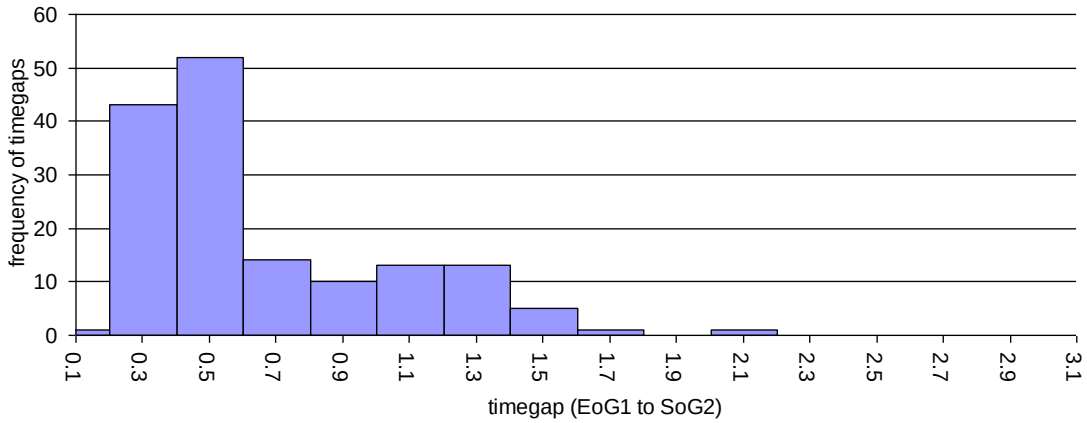


Figure 5-5: Timegap between two gestures . Histogram. Timegap is measured from end-of-gesture to start-of-next-gesture in a group of gestures that belongs together

From measurements of the corpus it was found that generally actions that follow within 2 seconds of each other could potentially form a group. However the criteria for which individual actions make up a group are not known before considering the utterance. For example the sentence “...take three cards for yourself...” (03.xml, t=2431) is different from “...you deal three cards to each player” (11.xml, t=1240). One time the instructor refers to 3 actions and, another time, to 6 actions in this two player game. Therefore the grouping algorithm devised for this corpus proposes more than one possible group of actions and leave it to a later stage, when the verbal instruction is considered, to choose the right group for unification. This is called a group “hypothesis”. All group hypotheses are stored in the multi-modal integration algorithm and the one that fits to the utterance will be used.

So far investigations into dealing cards found that two criteria for grouping were sufficient.

1. If the objects involved in the gestures share the same location or

2. if the objects involved have been manipulated in a similar way, i.e. turned over or moved, they potentially form a group.

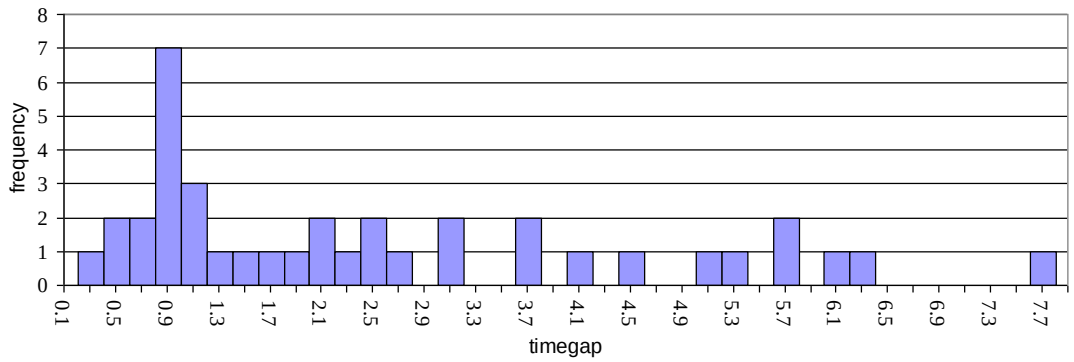


Figure 5-6: Timegap between two gestures-groups . Histogram. Timegap is measured from end-of-gesture-group to start-of-next-gesture-group. Note that there is often only a timegap of less than a second, which means timing information alone is not enough to perform grouping, and semantics i.e. the type of gesture is required to group gestures.

The grouping algorithm can not rely on timing alone, since figure 5-6 demonstrates that there is often less than 1 second between two groups that describe different action primitives. The only way to distinguish these groups is by looking at semantics, i.e. type of gesture and location.

From a theoretical view these grouping principles coincide with some of the Laws of Organisation in Gestalt theory (Wertheimer 1923). For example the proximity law, which states that objects or events that are near to one another (in space or time) are perceived as belonging together as a unit. Once candidate-groups of actions are established, the next step is to determine which utterance corresponds to which group. One approach is to consider temporal relations shown in section 5.2.4 .

5.2.3 Grammar for Gestures

A series (group) of words form a sentence and a grammar can be defined for it. The same can be said for a series of gestures:

A series of gestures can also be written as a gesture grammar

Figure 5-7 shows a CFG implementing the two gesture grouping rules mentioned earlier. An interesting question is: if there is a grammar for every modality (in this case gesture and language), is there a multi-modal grammar? Could it define multi-modal integration? This hypothesis is not answered in this thesis, though it presents an interesting thought for future investigations.

```
GG   → GGTT | GGTH | GGMT |...
GGTT → TT GGTT
GGTH → TH GGTH
GGMT → MT GGMT
TT   → turn at-hand
TT   → turn at-table
MT   → move from-table
```

Figure 5-7: Example of a right-recursive context free grammar for gestures. GG=gesture group, GGTT=gesture group of turning gestures in the hand, GGTH=gesture group of turning gestures on the table...

CFG Grammar for gesture recognition has been used in the past. Recognition with CFG is often combined with HMM. (Ogale et al., 2005) looked at recognition of a sequence of full body motion. However, usually only a single modality is considered. In the case of multi-modality, the CFG must be build so that the output is a group of gestures that are on the same level as a language primitive.

5.2.4 Investigation of Timing for Linking Gesture Groups to Language

In the collected corpus of card-game instructions, instruction-gestures can start before, during and after a corresponding verbal utterance. Figure 5-8 shows an example where the gesture-group G2 starts before the corresponding utterance U2. Table 5-2 show the transcription corresponding to figure 5-8.

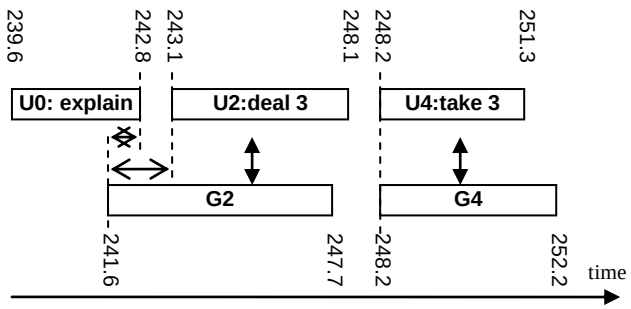


Figure 5-8: Timing Diagram This figure shows three incoming utterances (U0,U2,U4) and two incoming gestures-groups (G2,G4). The timestamps of start and end are given in seconds (timeline not to scale).

EXAMPLE DIALOGUE (SESSION 03 FROM MIBL CORPUS)

No	Time in sec.	utterance text or gesture semantics
U0	239.6-242.8	"I will just explain how you deal the cards"
U2	243.1-248.1	"er what you do first of all is.. er you deal three cards for yourself face down"
G2	241.6-247.7	move(D/5,C/2,H/QQ, Stock , Temp2)
U4	248.2-251.3	"and I will take three"
G4	248.2-252.2	move(D/QQ,D/KK,D/AA, Stock , Temp1)
...	…	…

Table 5-2: example Dialogue

In order to explore the possibility of using timing for linking action-groups with their corresponding utterance, the relative timing of their onsets and offsets was analysed. By creating a histogram using the data set-1 of the MIBL corpus, it is possible to see the relationship between start-of-speech vs. start-of-gesture-group, see histograms figure 5-9 and 5-10.

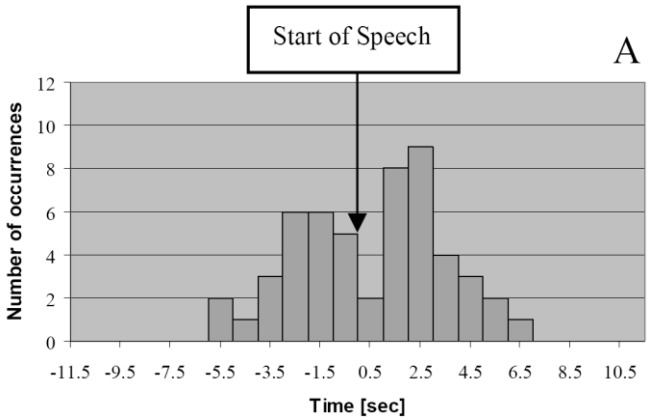


Figure 5-9: Histogram of the time intervals between start of speech and start of gesture.

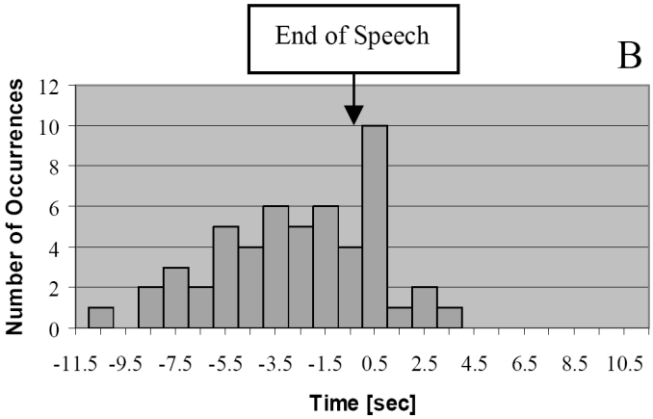


Figure 5-10: Histogram of time intervals between the end of speech and the start of gesture. Only gestures associated with speech events are plotted.

Figure 5-9 shows that gestures never start more than 5.5 sec before speech starts. Figure 5-10 shows that gestures never start later than 4 sec after corresponding speech ends. These observations suggest that a time window around the speech duration could be used to group speech and gesture. The time window borders are based on the maximum extends of the histograms. A graph that compares end-of-speech to end-of-gesture is not shown here, because potentially an action can take a very long time, and there would be no useful correlation.

5.3 Multi-Modal Integration Algorithm

5.3.1 Time-Based Integration

Results in the previous section suggested that a time-window-based method could be used for pairing speech with gesture. In figure 5-10, the markings in diagonal strips are time-windows. If a gesture group starts within the time window of a utterance, then the utterance and gesture-group could be paired.

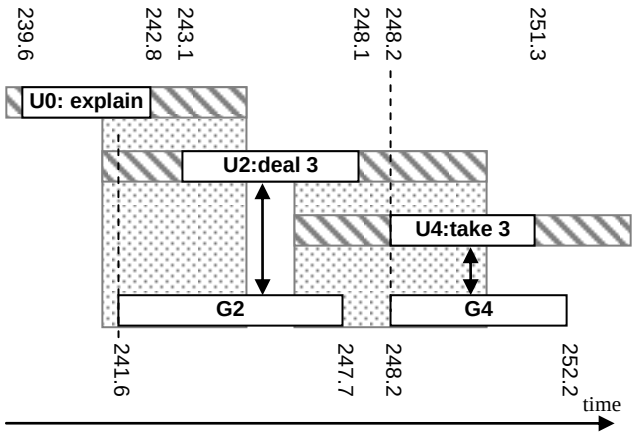


Figure 5-11: Time windows: This figure shows the three utterances with their corresponding time-window. If a start-of-gesture falls within that range, it is a candidate for pairing with the utterance.

However, utterances often follow up very closely behind each other in free flowing speech. In such a case, time-windows tend to overlap. The time-window overlap is indicated in figure 5-11 as a grey zone. Only 40% of start-of-gesture times do not fall in a grey zone and allow an unambiguous pairing. If, in ambiguous cases, the pairing is done with the nearest neighbour a rate of 78% of correct pairings is be achieved when compared to manual transcription (the remaining 22% are incorrect assignments). A nearest neighbour is found by comparing if the start-of-gesture is nearer to the end of the previous utterance or to the beginning of the next utterance.

The experiment was carried out by using the dealing-phase of the collected corpus. The figure of 78% can appear as a good result. However the remaining 22% of erroneous groupings can cause problems during semantic integration (unification). If the erroneous groupings are not rejected by the unification, then the robot would learn incorrect information. In a symbolic system this has to be avoided at all costs. Therefore it is

worth seeking an algorithm that can pair gesture to language without error, ideally 100% correct before unification.

5.3.2 Semantics for Multi-Modal Data Integration: Algorithm and Results

Investigating the erroneous groupings results from the nearest neighbour approach suggests that it may be possible to achieve perfect pairing by using semantic information, e.g. comparing the action referred to in the utterance with the action type in the gesture. The main verb in the sentence indicates the action. In conjunction with the object of the sentence the action semantic "*primitiveverb*" can be inferred, see extract of the grammar below. Parsing the sentences given in table 5-3 would result in U0(explain) having no primitive-verb, U2(deal) would be mapped to move and U4(take) would also be mapped to move.

```
PrimitiveVerb [
         (move) {<primitiveverb move>}
         (pull) {<primitiveverb move>}
         (drag) {<primitiveverb move>}
         (put)  {<primitiveverb move>}
         (take) {<primitiveverb move>}
         (turn) {<primitiveverb turn>}
         (turn them over)      {<primitiveverb turn>}
                (over) {<primitiveverb turn>}
         (flip) {<primitiveverb turn>}
         (deal) {<primitiveverb move>}
        ...
]
```

Table 5-3: simplified extract of the grammar assigning of the semantic primitiveverb. This grammar was created manually (pre-programmed).

The "primitiveverb" is a semantic category of what type of action is going on. Comparing the primitiveverb from the language with the type of action in the gesture enables semantic testing if the gesture is linked to the utterance. i.e. if the utterance is about moving a card, then the gesture can only be about moving a card, not turning a card.

The new algorithm applied primitive matching only in cases of uncertainty, when the start-of-gesture lies in an overlapping time-window. The nearest neighbour method ranks which one of the two utterances is considered first.

Some utterances in the corpus don't have action verbs. For example 03.xml/2396-2428:"I will just explain how you deal the cards". In a case where two utterances follow very closely behind each other, the grouping should be rejected if the action-verb

is missing. The complete algorithm using the concepts described in this section is presented in table 5-4:

```
consider the last two utterances
if:gesture starts outside overlapping window
{
        if: gesture starts in window[last]{
                found gesture-utterance match
}
        if: gesture starts in window[last-1]{
                found gesture-utterance match
}
}else:gesture starts in an overlapping timewindow
{
        choose the nearest utterance to the gesture
        if: the semantics to nearest neighbour match {
found gesture-utterance match
}else: semantics don't match {
       consider semantics of other utterance
       if: other utterance semantics match{
       found gesture-utterance match
       }
}
}
```

Table 5-4: Algorithm for integration of utterances and gestures

The algorithm only considers the two most recent utterances. The algorithm is called after an end-of-gesture-group is detected. On the data set-1 of our card-game corpus, it achieved only correct pairings, so that no false information was generated. The algorithm however rejected 11% of utterance-to-gesture groupings that should have been assigned.

Investigating the 11% of pairings that have been missed out, it was found that they are partly due to under-specification in the utterance, a missing action-verb, or due to grammar-errors in the robust parser. The current grammar attempts to split utterances at conjunctions like “and” or “then”, to avoid processing two instruction steps in the same utterance. This approach does not solve the problem in all cases. It is therefore likely that further work will reduce the number of rejected pairings.

5.3.3 Pointing Gestures in Multi-Modal Data Integration

Martin, J. C. (2005) provides an overview of Multi-Modal systems that involve pointing gestures. Evidence by Oviatt et.al. (1997), shows that pointing gestures coincide in timing closely to the reference word (here, there, etc) in the utterance. Oviatt found a maximum of 3 seconds between the deictic reference and the corresponding pointing gesture. Table 5-5 shows a complete list of deictic words and how often they occur in the MIBL corpus.

TABLES: DEICTIC WORDS FOUND IN THE MIBL CORPUS

DEMONSTRATIVE DEICTIC WORDS		POSSESSIVE DEICTIC WORDS		SPACIAL AND OTHER DEICTIC WORDS	
word	frequency	word	frequency	word	frequency
the	862	your	282	**Other**	
that	498	its	197	them	133
this	203	my	141		
those	85	ones	16	**Spacial**	
these	57	our	13	there	156
		their	3	here	69
		his	1		
		her	0		

Table 5-5: Deictic Words

Below is an example of the MIBL corpus:

EXAMPLE DIALOGUE (SESSION 11 FROM MIBL CORPUS)

No	Time in sec.	utterance text or gesture semantics
U0	162.2 -168.6	"what you have to do is er if you take one card from your er three cards"
U1	168.8-170.3	"and you have to either"
U2	170.4-172.2	"like im doing here"
G0	171.5-173.5	move(C/7, , Hand1 , Temp1)
U3	172.3-173.8	"you either match it with a card on **here**"
G1	173.9-175.6	move(D/7, Table , Table) (**pointing**)
...	…	…

Table 5-6: Example Dialogue

The example shows that the word "here" does not overlap with the pointing gesture, however the time of gesture start and the speaking of the word "here" (173.6 – 173.8) is only 0.1 seconds.

An algorithm to find the a near pointing gesture has been devised. It is consulted by the language primitive `ifloc` if the location semantics contain "`+here`" or "`+there`" rather than a specific location.

5.4 Discussion on Multi-Modal Integration

Unlike other proposed methods (Johansson 2001, Johnston *et al*., 1997) the algorithm does not perform a full unification to check for semantic compatibility. Full unification checks every primitive parameter for contradiction. I found that performance was improved by making grouping and linking algorithms simple, with a minimum of symbolic intelligence and rely on nearest neighbour for ranking. By a minimum of symbolic intelligence it is meant that only a check for compatibility, such as if the primitive-type is the same, i.e. move matches move, turn matches turn. If later, while unification is performed, the primitive parameters don't match (contradiction) then the user is asked to clarify the instruction. The improvement in performance can be explained by the fact that it is easier for the system to recognise different primitives than it is to recognise the correct primitive parameters. Nigay and Coutaz (1995) use the term "melting pots candidates" for the gestures and utterances that are in the buffer for linking, whereby the buffer is a memory that contains the most recent gestures and utterances. Coutaz has considered the problem in some depth.

Although the algorithm has not been tested in other domains, its approach of action-verb matching and nearest neighbour matching has the potential to be a quite general and robust method of multi-modal integration. The algorithm has been trained on the dealing-phase of the corpus, where actions occur particularly fast and frequently. In the game explanation phase (after dealing), the integration problem became less important, since actions were less frequent.

Oviatt (Oviatt *et al*., 2004) describes that there are two types of people when it comes to using a multi-modal interface namely "simultaneous" and "sequential" integrators. In our experiment this is not the case. In the domain of card-games, demonstrations can start before, at the same time and after speech. See histogram in figure 5-7.

5.4.1 Advantages of the integration algorithm

The integration algorithm shown in 5-4 is a late-fusion model, because it deals with information in symbolic format and on an utterance level. The advantage over early fusion models using HMMs or similar is that it needs less training data. Training data in this case is used to determine the limits from the histograms. It is generic as the form

presented in 5-4 does not show any context or domain. It can be analysed and understood easily compared to early-fusion models. The algorithm, when trained on the corpus, did not cause any erroneous pairings on the corpus.

5.5 Conclusions on Multi-Modal Integration

This work shows that it is possible to pair speech and gesture as occurring in unconstrained free-flowing human-to-human instruction dialogue. The proposed pairing algorithm combines timing and semantic information. An important property of this algorithm is that it does not make erroneous pairings.

Further work will explore if this algorithm allows processing unconstrained free flowing multimodal instructions through direct human-to-robot interaction, rather than by playing back teacher actions of a human-to-human corpus. In these experiments, the touch-screen interface will be the same; therefore the timing of multi-modal inputs is expected to be similar to that of human-human interaction. Tests have been carried out successfully and a robotic agent that can learn how to deal cards has been implemented, see chapter 8.

6. Corpus-Based Clause Grammars

Section 3.4.2 showed the form of the transcribed corpus in XML. Section 3.5.3 showed the language primitives that are extracted. The aim of this chapter is to introduce how corpus transcriptions are tagged to find language primitives and furthermore to show how the utterances are mapped to the language primitives. In a nutshell, the mapping from utterances to language primitives is done by a defining grammar.

6.1 Corpus Tagging

The transcription is stored as a XML file indicating which utterance belongs to which gesture. Each teacher explanation was tagged so that tasks and sub tasks are hierarchically divided. In this case the explanation has been divided with XML tags into the three game phases of dealing, game-play and counting points at the end. This could be referred to as *context tagging*. Inside the dealing phase 6 sequential instructions of moving and turning of cards (sub-tasks) were found. In the game-phase, the rules on pairing/capturing cards and the description of the ranking of cards were tagged manually. The tagging process also helps the developer to break down complex explanations into logical parts for which robot functions can be implemented correspondingly, step by step. An example below (`20.xml/912-955`) shows the tagging of the value-rule, which describes the value of a card in points. Example figure 6-1 shows the tagging and grammar of the pair rule.

```
<dealing>
...
</dealing>
<game>
   ...
   <value-rule>
      <tv t="912" until="955">
         and the jack queen and king become the eight nine and ten
       </tv>
   </value-rule>
   ...
</game>
```

Figure 6-1: xml-transcription. The utterance of teachers voice <tv> has been tagged as being part of the game-play <game> and as being an example of a <value-rule>. The value-rule, like in many card games, describes how many points the cards are worth.

The tagging process is also useful for automatically generating a grammar later.

```
<dealing>
...
</dealing>
<game>
   ...
   <pairrule>
   ...
   <tv t="2027" until="2060">
     ive won those cards there and now youll down to the three and then its your go
     <grammar>([ive (I have)] won those cards there)</grammar>
     <grammar>
          (and now [youll (you will)] down to CardCatNP:cn)
          {return( strcat(strcat("move=" $cn)  ",?,+side2:") )  }
     </grammar>
     <grammar>
          (and then its your go)
          {return("dm=turn-human")}
     </grammar>
   </tv>
   ...
   </pairrule>
   ...
</game>
```

Figure 6-2: xml-transcription with grammar. The utterance of teachers voice <tv> has been tagged as being part of the game-play <game> and as being an example of a <pairrule>. This example contains also the GSL grammar with language-primitive move() and dm() being passed to the knowledge base.

The example in figure 6-2 shows also that “I” and “you” is used interchangeably in explanations. Therefore the robot has to assume that it has to do all actions even the human says “I will” in his demonstration.

6.2 Clause Grammar

6.2.1 "One Clause One Primitive" Principle

Table 3-7 showed the verbs in bold font. Verbs can in most cases be tied to primitives in the form of VERB (ADJ1, OBJ1..). whereby the verb is a synonym or related verb for the primitive. For instance "deal" is related to the primitive verb-name "move".

The smallest natural language structure that contains a verb is a *clause*. By definition a grammatically complete clause must contain a *finite verb* and a subject. Therefore a grammar that maps natural language to primitives is easy to define if it is clause by clause. This means that sentences that consist of two primitives also have two clauses and should be split in the grammar definition. For instance, 17.xml/1434-1507 shown in the table above shows the word "capture" and "getting" in the same sentence, but split into two clauses, so it is possible to split it into the two primitives. In this example the primitives share the objects, therefore it would be wrong to split them completely, however in many cases the primitives are independent. Typically in sequences, when the phrase "and then" is used. This lead to the assumption that it is save to use a parser to cut utterances into clauses when certain sentence structures and keywords such as "and then" occur. This is described in more detail in section 6.2.1.2. . Lets first investigate dependent clauses before going on.

6.2.1.1 Clause relations

In English grammar *Dependent clauses* are clauses that can not stay alone as a sentence. Dependent clauses modify or add information of the previous clause. A special primitive (`clause_relation`) is necessary to show the dependency. The `clause_relation` primitive also shows temporal relations between clauses. A database of clause relations has been added:

CLAUSE RELATIONS

Clause	Language Primitive
`clause_relation(move,move,modify)`	further information about a move
`clause_relation(turn,turn,modify)`	further information about a turn
`clause_relation(FIRST,SECOND,sequence)`	the word 'after','then', ... indicates a sequence relationship of clauses
`clause_relation(FIRST,SECOND,first)`	the word 'first','initially' ... indicates a first-in-rule relationship of clauses
`clause_relation(FIRST,SECOND,last)`	the word 'in the end','finally' ... indicates a last-in-rule relationship of clauses

Table 6-1: Expressing relationships between clauses

By default, the robot assumes a sequence of primitives, whereby every clause/primitive produces new semantic knowledge. `clause_relation(_,_,modify)` is an exception. It indicates that a previously specified clause/primitive is modified.

An alternative representation of clause relations and semantic relationships in sentences in general is the Lambda Calculus. A short introduction of the Lambda Calculus was given in chapter 2.6.6. When comparing the Lambda Calculus to the structure presented here, it can be seen that the structure here (language primitives and parameters) is more simple and can be easily written down by a non-specialist designer without thinking about complex relationships between the words. One of the simplifications is that to uniquely identify and hold together the semantics, its timestamp is used in the background, rather than multiple nested brackets and variable definitions.

6.2.1.2 Parsing to cut utterances into clauses

Corpus utterances have been cut into clauses by the help of a natural language parser. Cutting is done if clauses are linked with words like “and”, “and then” or “so”. For identifying the end of a clause, The Apple Pie Parser by Sekine and Grishman (1995) provided most accurate results on the MIBL corpus. The Cass Partial Parser (Abney 1991) in conjunction with the Brill Tagger (Brill 1992) was tested on the corpus. It struggled with the spoken language and ambiguous expressions such as “take the five” like most parsers would, however the main reason why it was not used, is that it failed to identify the ending of clauses in many cases, compared to the Apple Pie Parser.

The Apple Pie Parser output was searched for 3 rules to detect and cut clauses: the phrases “*so*”, “*and then (SS*” or “*so then*”. A total of 914 utterances were considered in

the corpus tagged by <game> as being part of the first game-phase in data set-1, which follows after the dealing phase. Of these 914 utterances in 681 cases there was no "and" in the remaining cases there where

- 84 cases with "*and*" as the first word in the utterance, which means they don't need to be cut, because the clause is already at the beginning of the chunk
- 95 cases with "*and*" in a noun group which means they don't need to be cut because a noun group with "*and*"s is a list of nouns rather than a start of clause
- 54 cases remaining contained "*and (SS*"

6.2.1.3 Single tree structure

A problem of speech recognition is the fact that the speaker may pause before finishing the sentence (inappropriate end of speech). At this stage, assume that partial sentences are complete clauses. To cope with multiple clauses, they are linked at a higher level of the grammar.

The implementation of this grammar is written in Nuance GSL (Grammar Specification Language), which utilizes the slot filling concept. When a grammar rule (in this case made of a clause) is hit during speech recognition, variables (slots) are filled with values. These slots are in form of a first semantic interpretation such as "*go=forward*". Slots are the interface variables between the grammar and the application specific software that processes the interpretation. To preserve the order in which the clauses were said during interpretation, the semantic information of each clause is concatenated and passed to the reasoning system through a single slot. The single tree structure of context free grammar preserves order of semantics. This is achieved by structuring the whole grammar into a single parse tree. In other words the context free grammar rules must come together to a single grammar expression at the top. The top expression contains the slot. Now a user can arbitrarily give one or more instructions in one utterance while the order of the instructions is preserved in the order of the slot semantics.

6.2.2 Word Classes

In order to create a grammar that has over-generation only in appropriate places, such as generalizing over numbers or colours, the developer has to create semantic classes for words and phrases. Word-classes are semantic categories. For example the number of

cards (quantity) is a different class to the rank[5] of cards, see appendix A8. Using the same sub-grammar would lead to overgeneration in the wrong place. One could, for example, refer to "1 card" but not to a card with rank "1" since the smallest rank of a card is "2". These word-classes are then also used as a class in the knowledge representation scheme and as language primitive parameters, when passing information from the language recognition module to the reasoning system.

WORDCLASSES

Word Class Name in Grammar	Word Class Name in Knowledge Base	Members
NumberCat	rank	two,three,four,five,six,seven,eight,nine,ten,jack,queen,king,ace
ReturnNumber	n / value	zero,one,two,three,four,five,six,seven,eight,nine,ten,eleven, twelve, thirteen
SuitCat	suit	spades,clubs,hearts,diamonds,spade,club,heart,diamond
LocationN	location_label	"your black area","your hand","my hand","the middle","the table", "the deck", "the green area",...
CardCat	cardname	either or a combination of NumberCat and SuitCat

Table 6-2: Word classes

6.2.3 Full Corpus Coverage & Generalisation

Clauses have been grouped by their language primitive using the context tags during annotation of the corpus. The advantage of semantic grouping is that it ensures correct overgeneration at a local level. Semantic grouping also helps the grammar designer to structure and identify semantics, which initially looks as an overwhelming task when looking at a corpus of thousands of utterances. The definition of word-classes is an easy task for non-specialists in natural language processing. The resulting structure is a grammar template which is easy to convert into GSL grammar. The most trivial solution to convert a corpus into a grammar is to simply copy all transcriptions into the grammar. Hence all clauses become GSL grammar rules. This ensures that the grammar initially covers the whole corpus. This template is the starting point for the grammar designer.
Our aim is to reflect the corpus as accurately as possible. Even colloquial expressions are kept. For example:

```
14.xml/17428-17440: "thats right innit"
```

[5] "rank" refers to the ranking of cards, typically A, K, Q, J, 10, 9, 8, 7, 6, 5, 4, 3, 2

This is important for real world applications when the robot is used in a household. It is indeed possible to add sentences in good (corrected) English to the corpus, in a controlled way.

The primitives are now attached to each utterance in the grammar, manually, as shown in figures 6-3 and 6-4. This is a labour intensive task. Like the transcription, every utterance is considered. To go through the MIBL corpus to annotate a particular occurrence, such as a reoccurring action, in the text takes approximately 20 man-hours. Assuming annotation has already been done, the all primitives of the same type can be listed together and attaching the grammar is then quick. In the MIBL corpus the primitive "ifloc" occurred 91 times and "move" 163 times. If every grammar attachment takes 1-2 minutes, it is a matter of a few hours to do one primitive type.

Alternatively, this could be done automatically if the XML transcriptions have the utterances already annotated with primitives (semantics). Now, the bespoke word-classes can be substituted to create controlled over-generation. An example on how to achieve correct overgeneration (generalisation) is given below. First a version of the grammar without and then with generalisation:

```
Simple:
(if you have say a five)
{return("context_type=imaginary:" "ifloc=05,+hand2")}

Generalised:
(if you have say a CardCat:c)
{return("context_type=imaginary:" "ifloc=" $c  ",+hand2")}

Generalised with Noun-Phrase Grammar:
(if you have say CardCatNP:cn)
{return("context_type=imaginary:" "ifloc=" $cn ",+hand2")}
```

Table 6-3: simplified GSL-grammar showing the generalisation of the noun-phrase "a five". The word "say" refers to the fact that the situation is only imaginary and not happening at this moment. Example is part of 03.xml/3849-3911.

For every utterance a grammar and primitive is written into the transcription. This step in the grammar implementation is a time consuming but easy process. In order to expedite this process, a smart editor could be used that keeps track of word classes and suggests substitutions automatically. The smart editor could also suggest language primitives, based on previous related sentences. A related editor has been suggested by Wang and Acero (2001, 2006) and a graphical grammar editor has been suggested by Monaco (2002), although these do not have the full functionality required for the above task. I have developed the MuTra transcription tool (section 3.4.1) and incorporated a function to call a parser upon a keyboard button. Highlighted text becomes the input to

a custom parser (via batch-file) that replaces the highlighted text with the parser output. This is the basic support for automatic substitution suggested earlier. This functionality was used to test if for instance a grammar has already been defined earlier in the corpus. This constitutes a simple version of a smart editor. If it has been defined the NUANCE grammar testing parser nl-tool would return a result and also produce the necessary slots.

Once the grammar and slots for semantic interpretation have been designed, the output (slots) is ready for reasoning. The first step in reasoning is to resolve references. Here multi-modal information can be used.

6.2.4 Underspecified primitives

A short utterance often results in underspecified primitives have missing parameters. Missing parameters are indicated by question marks (‘?’).

A natural language parser will hit the interpretation of a shorter sentence before hitting the interpretation rule for the longer (more specified) sentence. Therefore the grammar must be tuned to put well specified grammar rules before underspecified grammar rules.

```
(?then I MOVE CardCatNP:cn onto the table)~1.0
       {return( strcat(strcat("move=" $cn)  ",?,+table:") )  }

(?then I MOVE CardCatNP:cn )~.99
       {return( strcat(strcat("move=" $cn)  ",?,?:") )  }
```

Table 6-4: Underspecified Grammar-to-Primitive matching: The first grammar rule specifies the location “table” while the second is underspecified. A probability reduction is attached to lower its priority in interpretation and the parsing order.

6.3 Overall Grammar Structure

After the procedures described table 6-8 have been completed, the grammar can be combined and compiled. This is an automatic process. This section describes how the grammar is structured, and the parser tools required for automatic combination.

Nuance GSL grammar is a context free grammar, which means that there is only one symbol on the left side and there is one or more terminal or non-terminal symbols on the right side of the grammar rule. Following this structure, the clause grammar of each clause and word classes need to be combined to a complete tree. This calls for a multi layered architecture of the grammar see (table 6-5).

Clause Link Level	← chain of clauses ("utterances")
Corpus Level	← all clauses of the corpus
Clause-Grammar Level	← clauses of the corpus with slot-filling grammar attachment
Phrase Level	← noun phrase grammar, word classes, verb phrases

Table 6-5: Levels of the grammar

6.3.1 Clause Link Level

At the top most level of this clause-based grammar is the linking of clauses (Clause Link Level).

A context free Clause Link Level grammar for combining one, two or three clauses (sufficient long for utterances) is shown here:

CLAUSE_LINK_LEVEL → CORPUS_LEVEL

CLAUSE_LINK_LEVEL → CORPUS_LEVEL CORPUS_LEVEL

CLAUSE_LINK_LEVEL → CORPUS_LEVEL CORPUS_LEVEL CORPUS_LEVEL

6.3.2 Corpus Level and Clause-Grammar Level

On the next lower level are the individual clauses of the corpus, i.e. the Corpus Level. Every clause of the corpus becomes a grammar rule at this level. This ensures that the grammar matches the corpus. This is part of the full corpus coverage design philosophy described earlier in section 6.2.3. At this stage the grammar is essentially a list of corpus

clauses. Even if there are no slots attached to some utterances in the corpus, they are now part of the language model and therefore a text interpretation can be obtained by speech recognition.

Some clauses have had a `<grammar>` tag attached in the XML transcription. These clauses are substituted in the list, so that the grammar from the XML transcription becomes part of the overall grammar. The substitution process is in two stages. First all content of the `<grammar>` tags is extracted (parsed) with `xml-filter.exe`. xml-filter.exe is a parser made for the MIBL project using the Expat[6] library. The extracted grammar is called the Clause-Level Grammar. In order to combine the Clause-Level Grammar with the Corpus-Level Grammar (list of corpus clauses), the Nuance tool `nl-tag-tool.exe` substitutes all clauses in the Corpus-level, that match, with clauses from the clause-level.

6.3.3 Phrase Level

The lowest level of the grammar is the phrase level. It is essentially a collection of word classes embedded in a noun-phrase grammar. A grammar for noun-phrases has been created to describe cards as shown in tables 6-6 and 6-7.

[6] Copyright of the Thai Open Source Software Center Ltd, Clark Cooper,Expat maintainers.
Corpus level grammar building in xml2grammar-test.bat

GRAMMAR	DET.	NOUN	LOCATION	AMOUNT	EXAMPLE
(ReturnNumber:n CardCat:c)	ns	$c	ns	$n	three cards
(DDD CardCat:c)	ddd	$c	ns	?	the seven, these sevens
(DDD)	ddd	?	ns	?	those
(CardCat:c)	?	$c	ns	?	ace
(NumberCat:n)	?	?	ns	$n	take three (missing article suggests number)
(DPD CardCat:c)	dpd	$c	ns	?	your card
(them)	them	?	ns	?	them
(them all)	them	?	ns	all	them all
(the DetAmountOf:n them)	ddd	?	ns	$n	the three of them
(it)	it	?	ns	1	it
(a CardCat:c)	a	$c	ns	1	a five of spades
(DetAmountOf:n DDD CardCat:c)	ddd	$c	ns	$n	all of these cards
(DetAmountOf:n DPD:p CardCat:c)	dpd	$c	$p	$n	all of my cards , any of my cards
(DetAmountOf:n DDD NumberCat CardCat:c)	ddd	$c	ns	$n	all of those two diamonds
(ReturnNumber:n more CardCat:c)	ddd	$c	ns	$n	three more cards
(DetAmountOf:n others)	ddd	?	ns	$n	two others
(DDD DetAmount:n CardCat:c)	ddd	$c	ns	$n	those two diamonds
(DDD DetAmount:n)~.9	ddd	?	ns	$n	those three (cards)
(the ones Location:l)	ddd	?	$l	?	the ones on the table
(DetAmountOf:n the ones Location:l)	ddd	?	$l	$n	all of the ones on the table
(DetAmountOf:n DDD CardCat:c Location:l)	ddd	$c	$l	$n	any of the cards on the table
(DDD CardCat:c Location:l)	ddd	$c	$l	?	those cards on the table
(DetAmountOf:n DPD:l DetAmount CardCat:c)	ddd	$c	$l	$n	one of your three cards

Table 6-6: GSL grammar of noun phrases. The 4 slots DET, NOUN, LOCATION and AMOUNT are returned to the knowledge base. Later, anaphora resolution is used to resolve what the noun phrase actually refers to. ddd = determinative demonstrative deictic reference, dpd = determinative possessive deictic reference. ns = not specified. The $ sign is passing a variable from a subgrammar. For subgrammars see table 6-7 and Appendix.

```
DetAmountOf
[
      (DetAmount:n ?of)             {return( $n  )}
]

DetAmount
[
      (both)            {return( "2" )}
      (all)             {return( "all" )} ;Universal
      (any)             {return( "any" )} ;Existential
      (ReturnNumber:n)  {return( $n  )}
]

DDD [
      (this) (these) (that) (those) (the)
]

DPD [
      (my)              {return("+hand1")}
      (your)            {return("+hand2")}
      (mine)            {return("+hand1")}
      (our)             {return("ns")}
      (his)             {return("ns")}
      (her)             {return("ns")}
      (its)             {return("ns")}
      (their)           {return("ns")}
]
```

Table 6-7: GSL-grammar, Simplified supporting grammar for noun phrases. For the full phrase-level grammars see Appendix A8

6.4 Summary on Corpus-Based Clause Grammars

The process of creating a grammar from the transcriptions is summarised in table 6-8.

Summary of Procedures

1. tagging of the tasks and subtasks (see section 6.1)
2. identification of primitives (see section 3.5.2, 3.5.3)
3. identification of parameters for primitives and word classes (see section 6.2.2)
4. organisation of word classes into an ontology (see section 6.2.4 on generalisation and 7.4)
5. writing of grammar for word classes (see 6.2.3 and Appendix A8)
6. extension of word classes grammar to noun phrase grammar (see section 6.3.3)
7. adding grammar to clauses in the corpus (table 6-3, 6-4)

Table 6-8: Summary of the procedure to create a clause-based grammar from the corpus

After transcription the utterances are grouped hierarchically by phases of the task and finally utterances are grouped by language primitives through context tagging (table 6-8 Point 1). Utterances are split by a parser so that sequential instructions/clauses are separated. A grammar is generated, containing all corpus sentences. During context tagging primitives are identified (Point 2). At this stage it also becomes clear what the structure of the ontology of the domain could be (Point 3,4). Ontological classes are created, which are then also used as sub-grammars for targeted overgeneration (Point 5) and as language primitive parameters. These sub-grammars are wrapped into noun phrase grammars (Point 6). To link the overall grammar together, all corpus sentences from the transcription are attached with a grammar rule (Point 7). The extraction of these attached grammar rules from the transcription into a complete context free grammar tree is an automatic compilation process and was described in section 6.3.

7 Knowledge Representation of Tasks

7.1 Rationale

Task planning and problem solving was a focus of artificial intelligence, when it was first invented; see for example Newell and Simon's (1956) "logic theorist" or "general problem solver". It was recognised from early on that task planning and execution is at the highest level in the architecture of autonomous systems. A limiting factor of such problem solver systems is that the search space quickly increases with complexity of the task. Although until now such problem solving systems are far from the level of humans, they are perfectly capable of solving simple tasks in household service robot domains. The key is that there are only a limited number of robot capabilities and objects in the environment (i.e. 1 knife, 2 sauce pans, 2 onions, 4 hobs...).

In recent decades a change on focus has occurred towards connectionist and behavioural intelligence. Much progress has been made by employing these approaches, such as neural networks, to perception and recognition. It was suggested by Brooks (1987) that planning should be avoided in robotics completely and the behaviour of a robot should be composed of local behaviour loops connecting sensors and actuators.

However, the same limitations apply also to connectionists, with increasing complexity of the task, the organisation of the information and the computational power causes problems and limitations (Brooks 1990).

In the short term, to make household service robots available, it is best to *combine the strength of both approaches* in a possible layered architecture. Namely using the strength of the statistical and behavioural theories in low-level reactive behaviour and for recognition and simple actuator control. And symbolic reasoning for planning actions and higher level behaviour.

The work in this chapter shows how knowledge can be represented and planning can be used at the top most level in the domain of card games. The challenge is to piece together human instructions in a usable form to carry out the task. We shall first investigate these human instructions.

7.2 Human Level Task Instructions

In corpus-based robotics, the application domain will reveal the instruction primitives and their level of complexity. In the IBL and MIBL corpus, it was found that these instructions are constructed for a listener with human reasoning capabilities. Indeed, the instructions found in the corpus reflect the assumption that human learners have reasoning capabilities and prior knowledge. For instance, the instructions contain no instruction on how to use the declarative information (marked with D in table 3-7 chapter 3.5.2). Teachers always assumed that the student knows what "dealing" is and what the symbols on the cards mean. The teacher assumes that the card-game-experienced student has the capability to reason using the acquired knowledge in order to decide the next move during the game.

In corpus-based robotics, if the application scenario would involve a small child as the receiver of instructions, the future child-robot would only need to be able to reason like a child, since the idea is that the corpus forms the starting point of the design.

A useful future service robot should have an adult-like (experienced) prior knowledge of the domain, for maximum efficiency during instruction receiving. A household service robot is meant to replace a experienced professional adult, the cleaner, butler or maid. A professional attitude would make a service robot usable for industrial and office use, where time is of essence. In a particular task domain, represented by a given corpus of instructions, a robot does not necessarily need to emulate all forms of human reasoning. Current models of human reasoning also show task specificity. An investigation into the required computational approach is required to determine the right framework.

The problem in designing a learning robot is the selection of a suitable representation of knowledge and of operations that can be performed on that representation. The following sections on Rule Frames, Ontological Reasoning and Problem Solving show how the knowledge is represented in MIBL. An overview of the system is given in Figure 7-1.

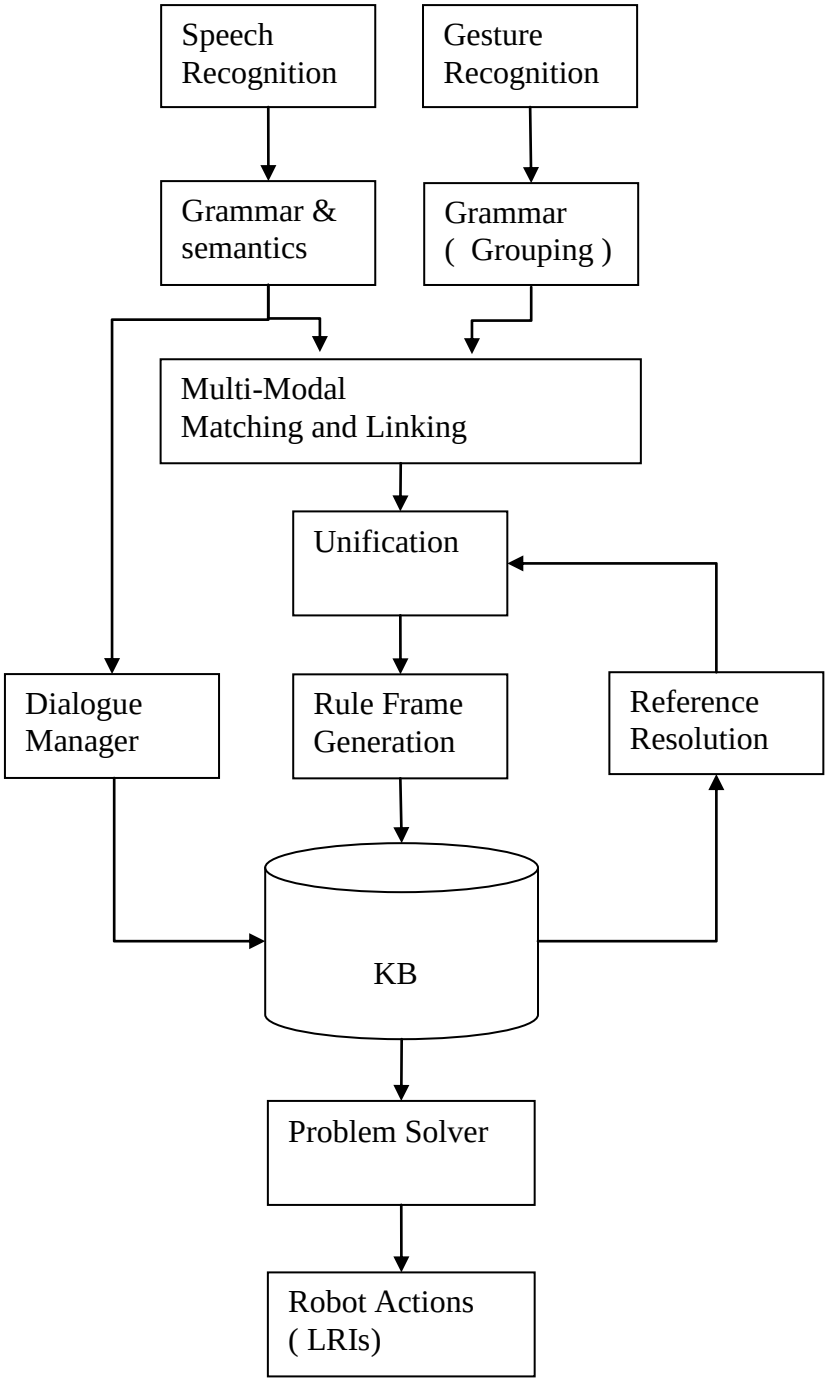


Figure 7-1: Overview of information flow in the MIBL system. Generally the information flow is from the inputs of Speech and Gesture at the top through to the output of "Robot Actions". These Actions include text-to-speech and manipulation of objects or changing the robots attention to initiate new recognition. Grammar has been described in the previous chapter 6 while the multi-modal module was described in chapter 5. This chapter deals with the remaining modules shown in this diagram. Refer to the Chapter titles for an explanation of the modules.

7.3 Rule Frames – an Intermediate Representation

7.3.1 Rule Frames

So far, it has been established in chapter 3.5 that human instructions are presented as primitives and these primitives have to be eventually converted to an executable program. The executable program will be presented to a problem solver for execution. If every primitive were complete and executable, this would be an easy procedure. The nature of human explanations however puts hurdles in the way of making this a straight forward procedure. The hurdles are listed here and examples can be found in the corpus given by references.

Human verbal and gestural explanations

1. include references to previously mentioned instructions and objects
   (03.xml/2540-2563 "you take these into your black area")
2. consist of a sequence of utterances, which belong together
   (03.xml/3919-3948 "...you got a three and a two..", belongs to 03.xml/3982-4012 "you take the three and the two because that's equal to five")
3. can be inconsistent or ambiguous
   (07.xml/1231-1254 "and i would win that card")
4. can be incomplete
   (03.xml/2540-2563 "you take these into your black area" leaves questions about how many, where are these, order of movement...)
5. may not be executable in the order they where explained
   (03.xml/3761... explains rule but forgets to say that the card has to be brought forward in the first explanation)
6. contain contextual information (not executable)
   (03.xml/2396-2428 "i will just explain how you deal the cards")
7. contain declarative information (not executable)
   (again 03.xml/3919-3948 and 07.xml/1231-1254)

This calls for an intermediate representation of the instructions between primitives and program, so that all problems and missing information can be resolved before a program is created. This is especially true for complex explanations where the human teacher is prone to making mistakes in the explanation.

To address the problems listed in 1-7 above, it is required to store information given by the teacher in an organised form. If it is in an organised form, the robot knows how to use the knowledge and determine whether any information is still missing. Since all the information is symbolic, it can be stored in a knowledge base. This knowledge base is organised to capture information about and dependencies between:

1. instructions primitives and their parameters
2. contextual information
3. declarative information
4. the robots prior knowledge

The human instruction primitives used in the MIBL project have fixed parameters making it easy to copy all parameters into a predefined frame. Complex rule explanation consist of a series of utterances with instruction primitives that all belong together, referring to a single rule. A frame is used to keep the rule together and in context.

The idea of storing knowledge in frames has been used widely in the past by (Schank 1975; Minsky, 1975; Bobrow and Winograd, 1977), also see section 2.6.3. The first systems such as Winograd's SHRDLU (Winograd, 1971) did only process individual sentences and frames where not required. The introduction of systems that collect primitives into some sort of frame came with the desire to write text story understanding systems for natural language. This started in the mid 1970s, see for example Wilks 1973, Rumelhart 1976, Schank 1975. Although the definition of terms has differed. Schank and Abelson 1977 (See section 2.4.4) report on scripts, which have the same properties as rule frames, namely they contain a sequence of instructions in the same context.

A rule frame must have a context property and at least one instruction primitive.

Complex tasks such as a card game consist of several phases. In the case of MIBL the phases are dealing, game and counting points. The context property (*context indicator)* describes in which phase the rule can be applied. In many cases it consists of more than one instruction primitive. The figure below shows a more complex rule frame for the capture rule in Scopa.

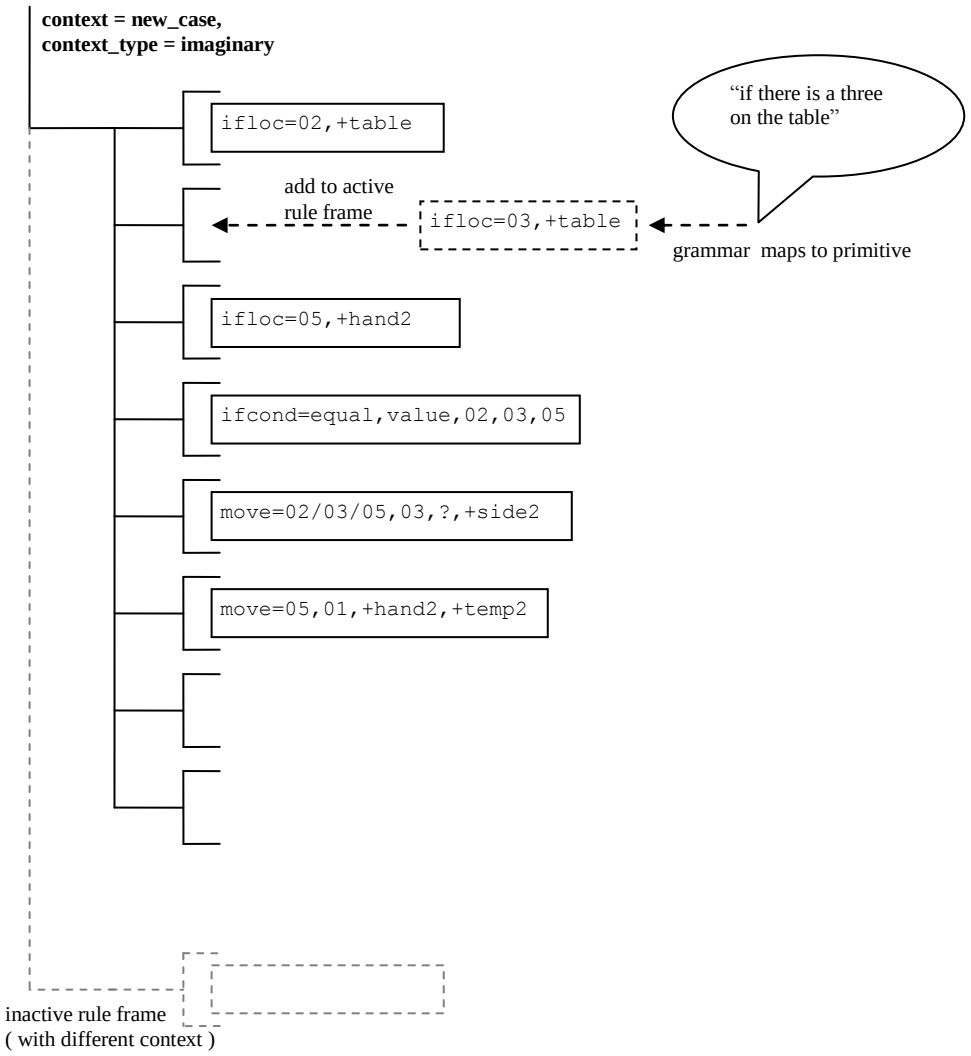


Figure 7-2: Rule Frame, instruction primitives and conditionals are connected together, since the utterances were in the same context. This rule frame is used to construct a function that the robot can carry out to play the game/ perform a task. If a teacher says and utterance it is added to the currently active rule frame. Context primitives can create new rule frames or switch between them. If there are question-marks left, or ambiguities, the robot can clarify information with the teacher before creating the new robot function.

Every time a user says and utterance which contains a instruction primitive, the primitive is added to the currently active rule frame. In general terms, a rule frame is a collection of hints on how the complete rule may be constructed. The problem solver has to determine how the rule works exactly.

A rule frame may contain *conditionals.* These have to be satisfied before the rule can be applied. In the MIBL project the *conditionals* are the primitives `ifloc` and `ifcond`. These typically come from game rules like "if you have a five you can match that five with one on the table…". However *conditionals* are very general and also apply to other

domains, for instance “if there a no more bin bags you need to …”. These conditionals could be compared to (Schank and Abelson, 1977) script header.

Additionally to *conditionals* a rule frame contains and a sequence of *instructions* that have to be carried out. These instructions will be carried out if the all *conditionals* are met. For instance figure 7-2 shows two `move` action primitives, which are the instructions of the rule frame. They will be carried out if there is a “2” on the table, a “3” on the table and a “5” in the hand of the player. Furthermore the condition 2+3=5 must be met by considering the values of each card. But how to generalise the rule and how to infer from the name to rank to value of a card, is not straight forward. This will be described in the next in section 7.4 when discussing ontological reasoning.

Every rule frame and rule frame instruction is given a unique index in the knowledge base (see figure 7-3 “move635”). To every instruction the noun phrase semantics (`np`) , the time stamp (`timestamp`) when it was recognised and the type (`instruction-type`) are also stored into the frame.

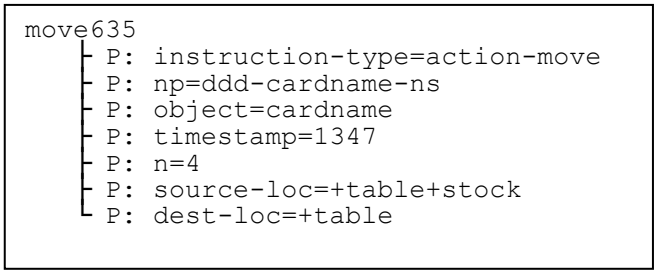


Figure 7-3: single Rule frame Instruction as it appears in the knowledge base

7.3.2 Scope of the Rule Frame notion

Since the idea of storing knowledge in frames has been used widely in the past, it can be hypothesised that rule frames work for many different domains, not only for the card-game Scopa. A different domain merely requires the implementation of different primitives. With the currently implemented primitives, one could already teach variations of fishing-type games, where some cards need to match in order to score.

7.4 Applied ontological reasoning

The exact structure and implementation of the ontology used by the MIBL robot is described next. For an introduction to ontologies, see section 2.6.4

7.4.1 Implementation of Ontology

The robot has an innate prior knowledge of playing cards and their properties. Properties are attributes of a class. Classes are structured in a tree taxonomy. For example a playing card is a 3D-object. A 3D-object has coordinates. See figure 4.

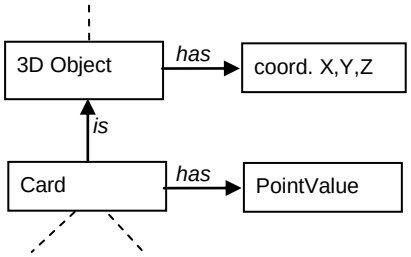


Figure 7-4: Extract of the ontology of cards for the MIBL reasoning system

The modelling of this ontology closely follows Smith (2006) and Spear (2006), who suggest ontology design based on Basic Formal Ontology (BFO). Essentially the `is_a` relationship indicates classes and sub-classes. A "Card" is a "3D Object". Now, classes can have properties. For example a "Card" often has a value in points, in a card game. Relations to properties are called `has_a` relationship indicates properties. Properties are inherited. For example "Card" inherits the property of coordinates (see figure 7-4). Currently multiple inheritance is not allowed. However, multiple ontological trees can be combined. Properties can be filled with values, which are defined as classes themselves. For example, a house has_a colour, whereby colour is defined as a class itself. Its subclasses are green, blue, yellow…

The implementation of the knowledge base, which includes the ontology as its backbone was done in Prolog[7]. Prolog is a declarative language, which makes the implementation simpler. Prolog allows the addition of code during runtime. New `is_a` and `has_a` relations are created as the robot learns. See below an extract of the MIBL code:

[7] the Sicstus Prolog 3.10 engine was used and interfaced from C. Prolog is based on first-order logic. It is a declararive language such as SQL or LISP.

```
is_a('face_card','rank').
is_a('cardinal','rank').
…
is_a('JJ','face_card').
is_a('QQ','face_card').
…
has_a('object3d','X').
…
has_a('cardname','rank').
has_a('cardname','suit').
…
```

Table 7-5: extract from the implementation of the ontology in Prolog

For further reading on Prolog, see section 7.9.2 . Actual cards that are present on the playing table are instances of classes. Because of the nature of the implementation, where the name of a class is the index of the table in the database, a class name must be unique.

```
is_a_instance('S/AA','cardname').
```

Instances inherit all properties from the class they are derived from. Classes are templates for instances. Instances are not part of the tree taxonomy directly. They are copies.

This representation system allows storing of the current situation and factual knowledge about the robots world. The previously described primitives that refer to a fact are manipulating this knowledge. For example the fact that the eight has been removed from the game translates into the Prolog statement:

```
forall(
   get_property(INSTANT,'rank',08),
     (delete_instance(INSTANT))
).
```

The "value" of a property is the terminal symbol in the created ontology.

```
property_data(INSTANCE_NAME,PROPERTY,VALUE).
property_default_data(CLASS,PROPERTY,VALUE).
```

Default property values is innate knowledge of the prototype of the object. For example a playing card "2" usually has the value of 2. Or a spades is "black". The idea of prototypes to represent initial assumptions has been used many times when more

specific information is absent. For example (Minsky, 1975) or Schank's Dependency Primitives (Schank and Abelson 1977) . Winograd also defines prototypes in KRL (Bobrow and Winograd, 1977).

Table 7-1 presents the ontology implemented for MIBL not showing instances.

```
root
  object3d
    P: X=
    P: Y=
    P: Theta_Y=
    P: location_label=
    cardname
      P: value=
      P: rank=
      P: suit=
      suit
        S
        C
        D
        H
      rank
        face_card
          JJ
          QQ
          KK
          AA
        cardinal
          02
          03
          04
          05
          06
          07
          08
          09
          10
  context
    P: current-context-type=
    P: current-context-name=
    raised-issues-stack
      P: current-issue=none
  dialogue
    P: state-vector=[greeting,none,human,none]
  coordinate
    X
    Y
    Theta_Y
  location_label
    +table
      P: state-vector-index=2
    +temp1
      P: state-vector-index=5
    +temp2
      P: state-vector-index=6
    +table+stock
      P: state-vector-index=1
    +stock
      P: state-vector-index=1
    +hand1
      P: state-vector-index=3
    +hand2
      P: state-vector-index=4
yes
```

Table 7-1: MIBL Ontology, without instances

Example of a Rule Frame as it is stored in the MIBL knowledge base using the ontology functions:

```
3          Rule217
3            P: phase=playing
3            P: timestamp=3554
4             IfLoc635
4               P: instruction-type=ifloc
4               P: np=a-KK-ns
4               P: n=1
4               P: location=+hand1
4               P: object=KK
4               P: timestamp=3761
4             IfLoc763
4               P: instruction-type=ifloc
4               P: np=ddd-KK-ns
4               P: n=?
4               P: location=+table
4               P: object=KK
4               P: timestamp=3761
4             IfCond399
4               P: instruction-type=ifcond
4               P: type=equal
4               P: compare=value
4               P: lhs=[a-?-ns,1]
4               P: rhs=[[a-?-ns,1],[?-?-ns,?]]
4               P: timestamp=3761
4             move240
4               P: instruction-type=action-move
4               P: np=ddd-cardname-ns
4               P: n=1
4               P: source-loc=+table
4               P: dest-loc=+hand1
4               P: object=_829
4               P: timestamp=3795
```

Table 7-2: MIBL Rule Frame From the MIBL Corpus 03.xml / Pairing rule.
The rule frame "Rule217" with 4 instructions.

7.5 Anaphora Resolution

Antecedent anaphora are references to explicitly mentioned nouns, earlier in the discourse, see Grishman (1986). According to Grishman (1986), anaphora resolution is one of the most difficult problems in Natural Language Processing.

The determinative demonstrative deictic references (DDD): *this, these, that, those* and *the* in the noun-phrase are indicators for anaphora. Further corpus references are determinative possessive deictic references (DPD): *my, your, our, his, her, its, their, ones*. And finally the word *them* is also treated as a reference to earlier mention.

A noun phrase grammar was defined to identify anaphora such as DDD, DPD. The information produced by the noun phrase grammar is shown in table 6-6 and 6-7. The grammar returns a tuple of information about the noun phrase consisting of:

```
[ Determiner , Noun , Location , Amount ]
```

This semantic information can be used to resolve the references. If a new object is introduced to the conversation, the noun phrase contains the determiner "a" or no determiner at all[8]. In this case no resolution is required. The noun phrase semantics are stored into the rule frame. If in the next utterance a DDD occurs, it is assumed that the noun phrase refers to the previously stored noun phrase. The implementation of the anaphora resolution is a series of rules like the one, just mentioned[9].

Every noun phrase tuples are stored in the rule frame, see table 7-2 property "np" for noun-phrase. The noun phrase tuple finds its way from the utterance to the rule frame as instruction primitive parameters. If the resolution algorithm is confronted with a DDD, the resolution is achieved by retrieving the previously stored noun phrase. The resolution process accesses the linguistic clauses in their formal format as rule-frame instructions like shown in table 7-2.

Here an anaphora resolution algorithm tries to identify the reference by looking at the previous instruction. It will jump over and ignore sub-dialogues and utterances which do not have instruction semantics. If a previous utterance and its corresponding rule-frame were identified, it is possible to recover missing information for the new rule-frame. For example the utterance "turn them over", does not say which cards need to be

[8] in the grammar implementation, no determiner has the symbol "ns" for not specified
[9] see code ref_res.pl in Appendix

turned over, how many or where they are. With anaphora resolution referring to a previous sentence, this information is recovered. Anaphora can be resolved by looking at two sources: gesture or to a previous utterance. In the MIBL software, gesture was not considered, future work could include gestures. References to resolve the noun-phrase from gestures is considered through multi-modal integration instead.

ANAPHORA RESOLUTION RULES APPLIED IN MIBL

Current Clause		Previous Clause		Case Description	Resolution Action
Det.	Object	Det.	Object		
a				introduction of new object and possibly new context	use object given in current clause
REF	'?'	a		reference to a previous object that is first introduced in the previous clause with "a"	use object given in previous clause
REF	not '?'	a		reference to a previous object that is first introduced in the previous clause with "a"	use object given in the current clause
REF	not '?'	ns		reference to a previous object that is first introduced in the previous clause without article	use object given in the current clause

Table 7-3: Anaphora Resolution Rules. For resolution an object must be referring back to its first instruction into the conversation. Clauses are dealt with in the formal rule-frame instruction format.
REF is ddd,dpd,them,it, or '?'

Once the previous rule-frame instruction is identified using the table above, the object of the conversation can be recovered. Further information about completing the new rule frame can be recovered as well. To come back to the example "turn them over", the question of how many cards need to be turned over can be identified by looking at the previous rule frame, if it also contains a parameter "n".

7.6 Unification

The process of multi-modal integration has been described in chapter 5. Figure 7-1 shows how unification follows after the multi-modal integration system. It is often regarded as being part of the multi-modal integration process with the last step in the integration being unification. Unification is the process of combining (unite) semantic information from different sources. The concept of unification exists in grammar (Shieber 1986) and in logic programming (Bratko 2000). In multi-modal systems, unification is performed between language and gesture primitive parameters.

The following 4 cases can occur as a result of unification:

UNIFICATION OF LANGUAGE PRIMITIVES

Case	Number of Solution	Description	variables
Completion	$n_s = 1$	A gesture and an utterance are individually incomplete, but complete each other.	all variables are resolved
Confirmation	$n_s = 1$	A gesture and an utterance are individually complete. When combining they match.	no variables exist
Contradiction	$n_s = 0$	A gesture and an utterance contradict each other, no solutions, unification fails	
Under-specification	$n_s > 1$	The gesture and language combined are still semantically underspecified. Therefore several possible candidates are returned	

Table 7-4: Unification possibilities. Where n_s is the number of solutions

In MIBL, unification is used for move, turn and pointing primitives. Parameter by parameter is compared between the language version and gesture version of the primitive. Each time the outcome is one of the 4 cases. This is known as a tautology, with action attached to all outcomes. In fact it is good practice to program algorithms in a fashion where each “if” statement needs an “else” statement so that the all cases combined are a tautology. This helps the developer to clarify its own mind and proves the algorithm covers all possible cases. This technique has also been used when designing the multi-modal integration algorithm.

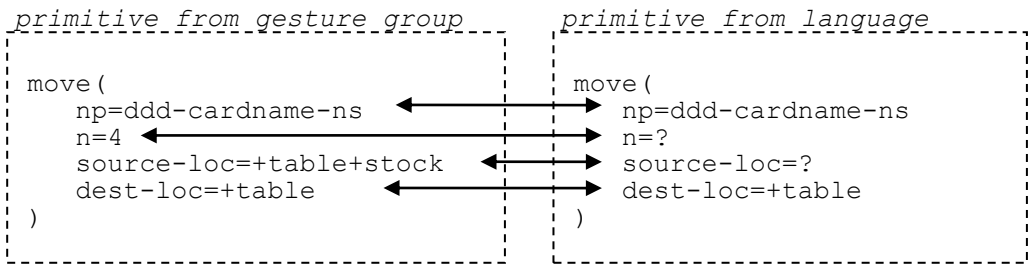


Figure 7-5: Unification process, missing information of the language primitive "deal the cards onto the table" is unified with the gesture group that was selected from multi-modal integration. Parameter by parameter is compared with the algorithm shown in figure 7-6. The implementation is in Prolog.

If the multi-modal integration algorithm firmly believes that gesture and language need to be unified, the selected candidates go through the unification process described in the flow chart below. Each primitive has parameters, and the parameters are unified individually. In the cases for under-specification or contradiction, a question can be raised to the user to obtain missing information, also see flowchart figure 7-6 with instruction "Raise question". Unification with integrated question to the user is also described by (Kruijf *et al*., 2008). Kruijf argues that robots can only understand the world around them by deliberately planning clarification questions. In the MIBL system this is realised by the Issue stack described in section 7.10.2.

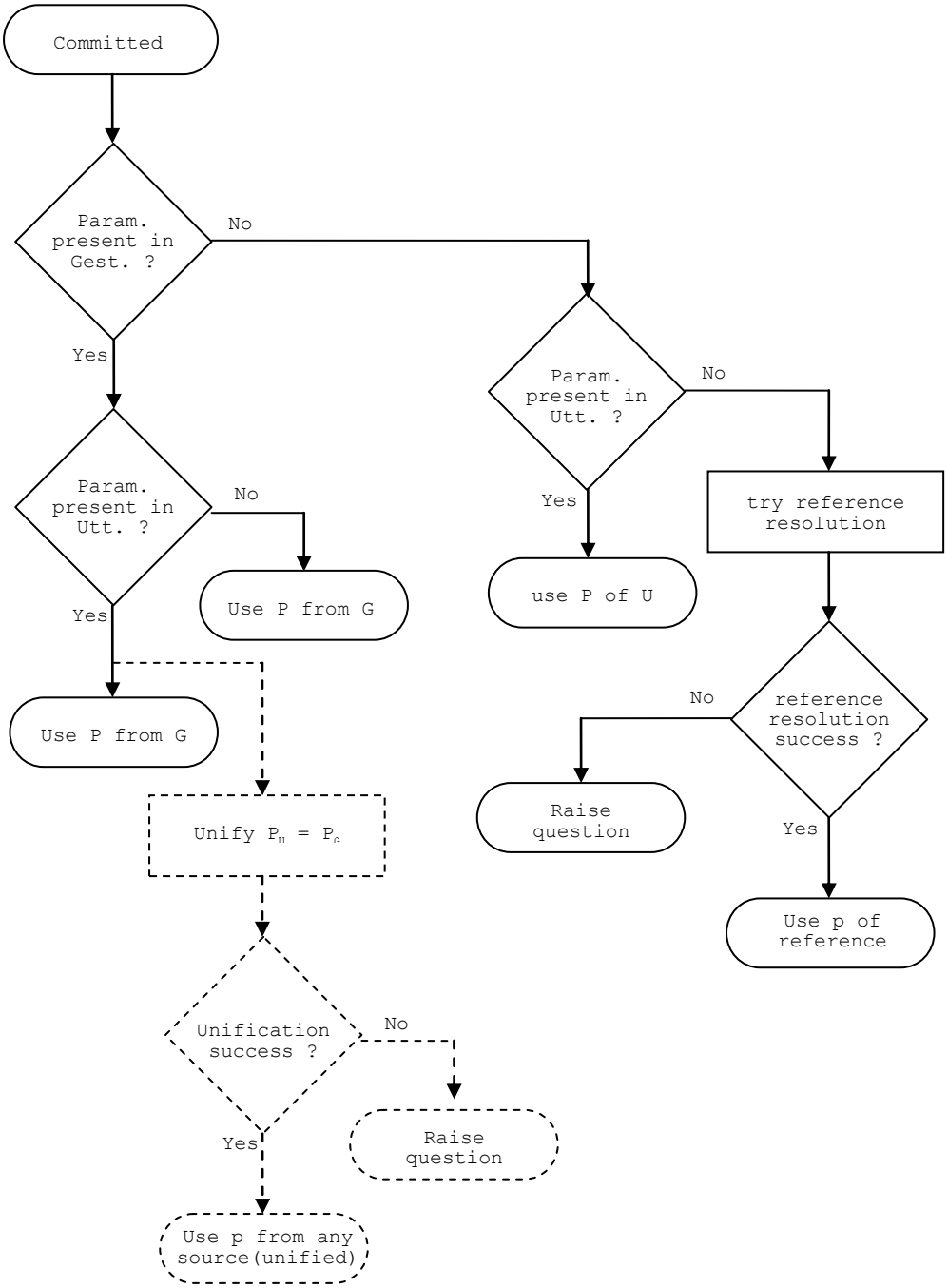


Figure 7-6: Process for unification of primitive parameters. Since speech recognition errors are more common than gesture recognition errors, the process believes gestures. An alternative method is shown in dashed lines. P=Parameter of a primitive, G=Gesture, U=Utterance

The unification algorithm has been tested through an integrated test by playing back the corpus, see experiment E3.1, E3.2 in chapter 8.5-8.6. The algorithm uses a conservative approach, it asks the user if there is uncertainty, thus its performance is trimmed to avoid false information to be stored in the knowledge base.

7.6.1 Mirrored Location References in Utterance and Gesture

A special case of primitive parameters is the location-parameter. A teacher explanation often needs to be mirrored to allow the robot to take the teacher's perspective. Or in general terms, the robot needs to imagine being the teacher. This needs to be considered when comparing location-parameters between gesture and language as well, because teachers used "you", "me", "yours"… interchangeably without paying attention. Therefore, by default, any location that is in-front-of the teacher must be mirrored to in-front-of the robot.

7.7 Initiation of Learning

7.7.1 Timing

Lower layers of a robotic system continuously receive sensor data and low level recognition processes often produce outputs at a high frequency, for example images are produced at a frame rate, in the case of MIBL, gesture data is produced with 10 Hz and low level recognition of actions can therefore output several times a second. The question is when is the best time to process this now symbolic data further for the unification, learning of rules and actions? This point in time t_D is limited to a minimum. Too early processing take into account incomplete gestures or utterances, too late processing (>10sec) will slow down and confuse the human-robot dialogue (not anymore real-time). The following limitations constrained and defined the point in time t_D to initiate learning:

- a gesture group has finished: $t_D = t_{End\text{-}of\text{-}Gesture} + t_{End\text{-}of\text{-}Group\text{-}Timeout}$
- an utterance has ended, and no gestures followed:
  $t_D = t_{End\text{-}of\text{-}Speech} + t_{SoG\text{-}2\text{-}EoS\text{-}Max} + t_{Max\text{-}Gesture\text{-}Length}$
- A gesture has ended: $t_D = t_{End\text{-}of\text{-}Gesture}$

The criteria and timeouts shown are taken from the timing histograms on multi-modal integration (Chapter 5.2.4 figures 5-7,5-8). A scheduler algorithm manages the calling of the unification and learning algorithms at the calculated time t_D. The scheduler algorithm performance was tested as part of the multi-modal integration system in chapter 5.3.2.

7.7.2 Overview of the unification and learning algorithm

1. consider most recent two unprocessed speech events
2. establish relationship between clauses (section 6.2.1.1) to check if a primitive is modified or if a new primitive needs to be created in the knowledge base
3. process new knowledge primitives
4. process new action primitives:
   - 4.1 group gestures
   - 4.2 filter out unfinished groups, reschedule t_D if unfinished group is discovered
   - 4.3 matching, linking and unification of action primitive with gestures
     (on success, add action primitive to rule frame)

if unification failed try learning without regarding the gestures

if a loop-indicator such as “each” is in the language multiply the new instruction

5. store information in rule-frame

The performance of the multi-modal integration (except step 4.4) was presented in chapter 5.3.2.

On a context change, i.e. a new rule is completed; the rule-frame is translated into a state-transition-rule, which completes the learning of the rule. Therefore the learning is an on-line process.

7.8 Problem Solver

7.8.1 Overview

Section 2.6.5 gave an introduction to problem solvers. The MIBL robot plans the application of a rule frame before carrying out the primitives. This is achieved by applying the rules that it learned by using a problem solver. On its turn in the card game, the robot looks at the cards and their position (`STATE_VECTOR_LIST`). This forms part of the initial state. The game rules that are made of rule frame instructions are applied as state transitions. The goal of the problem solver is to apply a learned rule successfully. The robot tries to apply the rules to different combination of available cards. The combination of possible cards and game rules form the search space of the problem solver. It is a dynamic environment, different in every game and depending on the rules. The IBL project proposed a planner to test the route through the city. In both projects, the planner helps the robot to check if the learned knowledge fits together to produce an output program that will complete the task successfully.

7.8.2 from Rule Frame to State Transition Rules

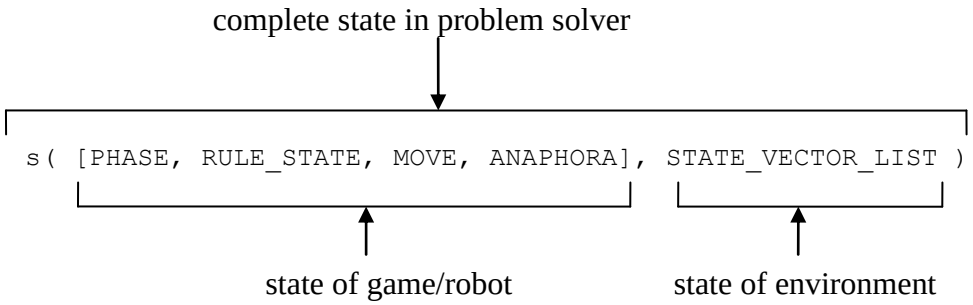
The rule frames are wrapped into state transition rules (STR) to allow the robot to predict the outcome of its actions. State transitions are the required building blocks for a problem solver. State transitions are a common tool in robot task execution; see for example (Lopes *et al*., 2003). A state transition rule consists of the entry state, rule frame instructions (RFI), low-level robot instruction (LRI) and the exit state.

```
str( entry_state, exit_state, LRI) :- RFI
```

Since the output from state transition rules is low-level robot instructions (LRI), the STRs are a form of translation between human-level instructions and robot instructions. The complete state of the problem solver consists of two parts: the state vector list describing the environment and the game/robot state vector.

On the robots turn the robot is initially in the following state:

```
s( [PHASE,initial_state,_,[]], STATE_VECTOR_LIST )
```



when trying to apply a rule the robot goes from

```
s( [PHASE,CURRENT_RULE,LAST_INSTR,[TUPLE_LIST,MATCHED_LIST]],
STATE_VECTOR_LIST )
```

to this state

```
s( [PHASE,CURRENT_RULE,INSTR,[TUPLE_LIST,MATCHED_LIST]],
STATE_VECTOR_LIST_OUT )
```

and finally, when all instructions of the rule frame have been successfully applied, the problem solver achieved his goal. The goal is defined in the problem solver by investigating the solution path and making sure that all instructions of the chosen rule frame are found in the solution path.

For example: CURRENT_RULE could be “Rule217” and LAST_INSTR and INSTR are actions from a rule frame, for example “move240” from table 7-2.

A key point of the system design philosophy is that in order to use rules that have been explained to the robot, the robot needs to constantly compare the current state of the environment with the precondition in the rule frames in order to derive the next valid step in its actions. This is realised using a problem solver. Once the next valid step has been found the robot can predict the consequences using the state transition rules. The

robot simulates the next step by using the state transition rules (production rules) which consist of rule frames.

The "PHASE" in the state vector describes the wider context. It is used to guide the problem solver to use only the appropriate rules for the given context. For the card-game system 3 contexts have been used: "dealing", "playing" and "imitation". The context switching is handled by the dialogue manager. "imitation" is a special, in a sense because it is used to temporarily do actions imitating the teacher.

When trying to apply a rule, i.e. going from state to state, an algorithm is used to put the rule frame into action.

1. check all *ifloc* conditions of the rule-frame
2. considering the cards selected in the *ifloc* conditions, do the *ifcond*,
   which usually is a comparison function between cards.
3. do all action instructions of the rule-frame

Firstly, the current state is examined if the necessary cards are in place (*ifloc*). This first application of the *ifloc* rules also collects a tuple-list of cards and their properties that are involved in the rule.

A tuple-list is necessary to preserve the reference to objects within a rule throughout the application of the primitives. For example "if you have say a five" "you can bring the five forward" This is a fact and an action, but the "five" is mentioned two times. This link must be preserved in the reasoning when applying the rule. The next step is to apply comparison functions to the tuple-list and the current state. If the comparison function is passed as successful the last step is carried out, which is doing the actions of the rule in sequence. First the actions are only simulated by modifying the current state and replying this outcome to the problem solver. If the problem solver selects this state the actions are actually applied by the robot. Within a rule-frame, the problem solver tries to carry out the functions in order of explanation. If this fails, the problem solver can try actions in a different order, since some human teachers fail to explain the rule in the right order to the robot.

7.8.3 Micro Planner

Every state transition in the MIBL planner (problem solver) a primitive is applied. In some cases an action primitive can describe a procedure that actually requires several actions, such as utterance 06.xml/709-738:

text: "and then we put four cards in the middle".

primitive: move(ns-cardname-ns,04,?,+table)

This primitive would require 4 pick and place moves. The possibility of doing these 4 moves is tested by the micro planner. The micro planner carries out the action (move or turn) card by card. It generates low-level robot instructions (LRIs) for every move, naming the specific objects involved.

7.8.4 Generalisation and References in Rules

It was found from the corpus that complex tasks are often explained using an example, which means that the robot needs a generalization mechanism. A reason for this explaining by giving examples could be that it becomes easier to reference to the various different objects (in this case cards) involved. A personal robot has to be able to learn from one or two examples of a task explanation. Asking for further explanations will annoy the user, since an experienced personalised service robot is not seen as a child in the user's eyes. It is an adult servant who should reduce the workload of the user. Furthermore, anyone who has used speech recognition knows that it can test the user's patience. Therefore, the robot must go to great length in order to generalise what it learned autonomously. It is difficult for a robot to find what the salient features of the situation are and it can therefore not easily induce a rule. This is called the "frame problem" (McCarthy and Hayes, 1969) and is one of the limitations that remain unsolved in artificial intelligence. The frame problem can only be resolved by pre-programming the right actions in the context that the robot encounters, in this case card games.

It is possible to rely on so called "hasty induction" of the rule without proves, see (Flach *et al.*, 2006). If a user says "if you have a five in your hand", Prolog will treat this five as a placeholder in its representation of the instruction. This implicitly

implements the concept of generalization. Practically, this is equivalent to storing "if you have card A in your hand, which is in this example named 5". This may be how humans learn game rules, and they are often stopped later on by the teacher during test games if the generalization was flawed. However, the limited task domain is an advantage that helps making correct generalizations. While explaining the capture and the pairing rule of the game, all subjects used actual cards as examples or at least gave examples set in an imaginary situation.

Below is an extract from the logfile that was written when trying to apply the pairrule after learning it from transcription 15.xml :

```
do_ifloc/5 passed for: IfLoc635 with item: S/QQ
do_ifloc/5 passed for: IfLoc763 with item: C/JJ
do_ifloc/5 passed for: IfLoc763 with item: C/QQ
do_ifloc/5 passed for: IfLoc763 with item: D/05
do_ifloc/5 passed for: IfLoc763 with item: H/QQ
TUPLE_LIST = [[S/QQ,JJ,4],[C/JJ,JJ,2],[C/QQ,JJ,2],[D/05,JJ,2],[H/QQ,JJ,2]]
find_references/3 MATCHED_LIST: [[S/QQ,lhs,9,4],[S/QQ,rhs,9,4],[S/QQ,rhs,9,4]]
find_references/3 MATCHED_LIST: [[S/QQ,lhs,9,4],[S/QQ,rhs,9,4],[C/JJ,rhs,8,2]]
find_references/3 MATCHED_LIST: [[S/QQ,lhs,9,4],[S/QQ,rhs,9,4],[C/QQ,rhs,9,2]]
do_comparison/3 (equal,value): ifcond match equal,value passed S/QQ=C/QQ
do_instruction/6: TYPE=action-move INSTR=move240 OBJECT=_4577
LRI=[move(C/QQ,+table,+hand2),say(i can move this card)]
```

Table 7-6: Log file from Rule Application From the MIBL Corpus 15.xml / Pairing rule.

7.8.5 Game Strategy

As stated earlier, the problem solvers goal is to successfully apply a learned rule (goal state: `s([…,done_rule,…,…],…)`). This is the end of the robots turn to play. The robot makes no attempt to plan the game until the end, because it would have to guess what cards the other players have or what is next in the stock pile. This is called a partially observable game.

The robot has no preference on which rule to apply first or which card to prefer. It there is more than one solution from the problem solver, it will just apply the first solution and discard the others, unless it failed to execute the first solution.

Adding a preference which solution to choose is a matter of game strategy. Adding a preference reduces the search space. Reduction of the search space was not required for the application of the Scopa card game rules of the MIBL project.

However, without any optimisation at all, the problem solver can easily get stuck in an endless loop. If two instruction primitives reverse their effect, putting a card on the table

and picking it up straight after, just to show your opponent what you have got, is a typical example. The problem solver may suggest that these actions have to be carried out several times which is actually not true.

Some tasks that have a large amount of rules and physical objects in them can not be solved without an optimisation. The computational expense of the micro planner is doubled with each additional object or rule.

7.8.6 Low Level Robot Instructions

LIST OF LOW LEVEL ROBOT INSTRUCTIONS

LRI	parameters	description
move	(%1,%2,%3)	robot moves a single object %1 from location %2 to location %3
turn	(%1,%2)	turn object %1 around %2 degrees
shuffle	()	shuffle all the cards and return them to the stockpile
say	(%1)	say %1 using the text-to-speech system
grammar	(%1)	swap recognition grammar to %1
system	pause	stop the time in the system (used for question answering in corpus-playback)
exit_program	()	shutdown the robot
dm	schedule_ gesture_ recognition %1	the recognition system (unify-and-learn) predicts that attention for further recognition and processing (unify-and-learn) is needed at time %1 in the future
none	()	Do nothing for the moment

Table 7-7: Low Level Robot Instructions

7.9 Advantages of Implementation in Prolog

7.9.1 Logic Programming

Prolog is based on first-order predicate logic, making it easy to describe facts and relationships. Prolog is a declarative programming language, in contrast to imperative programming languages. In declarative programming, statements are descriptions of a logical goal, rather than stating instructions on how to carry out the search in the knowledge base. One can declare the logical goal and the Prolog engine will carry out the search by trying to resolve the unknowns in the query. This resolving process is the core of the Prolog engine. It incorporates SLD[10] resolution (Linear resolution with selection function in definite clauses), see Kowalski and Kuehner (1971) for detailed explanation.

For instance, if a Prolog program consists of the single statement

animal_name('cat1', 'maumau').

and one would like to write a program to find the name of 'cat1', then this is simply done by writing

animal_name('cat1', N).

Prolog will answer

N = 'maumau', yes.

Prolog Unification. Prolog attempts to prove *animal_name('cat1', N).* by attempting to find and unify all "knowledge" in its database with this term. In this case there is only one relation in memory, which matches. This matching process uses unification, which means that the goal and the knowledge is unified, resulting in the unification of N = 'maumau'. Prolog will answer 'yes' when a logical goal has been successfully proven.

7.9.2 Storing Knowledge in Prolog

In order to represent knowledge in Prolog, one can simply state facts and their relationships. For example *colour('cat1' , black).* is a valid Prolog statement. These relationships were utilised to organize knowledge in a hierarchical tree-taxonomy. The modelling of this tree-taxonomy is inspired by Smith (2006) and Spear (2006),

[10] SLD resolution stands for **S**elective **L**inear **D**efinitive clause resolution

mentioned in section 7.4 . Governed by *has-a* and *is-a* relationships a tree of objects and their properties can be devised which constitute the robots knowledge base. These are easily expressed and can be queried in Prolog, see this example of a Program:

is_a('+table','location_label').
has_a('object3d','location_label').

7.9.3 Search Space Reduction

An inherit problem of logic programming is that the amount of computation time required can grow exponentially (depending on the algorithms used) with the number of symbols in the knowledge base.
Humans use context and attention mechanisms to filter out unimportant information, this principles was applied here. Attention mechanisms are applied to reduce the search space. In the case of MIBL, only the latest two utterances are considered for processing, which is in effect focuses attention to recent events and therefore reduces search space. Furthermore the `context` branch of the knowledge base is a pointer to the currently active rule. This reduces search space again.
The robot has a memory that remembers all gestures that have occurred. The gestures that have been used for learning already are marked. During a context change all past gestures are marked as used and won't be used again for learning.
In practice, learning rules of a single card game does not represent a computational burden in terms of search space of the knowledge base. There are the 52 cards all past language and gestures and rules in the robots knowledge base, which make up hundreds of symbols in total. It can be hypothesised that a single household task of future service robots will not need more symbols and data than in a card game.

Considering livelong learning however, the robot should delete used gesture and language events to reduce the search space. Rules should be stored on a permanent memory and loaded depending on context.

7.10 Dialogue Manager

In natural language processing a mechanism that detects and guides the discourse of the conversation is the dialogue manager. Traditionally, the dialogue manager is a state engine of some form (Spiliotopoulos *et al*., 2001). Modern natural language tools such as Nuance NVP Builder allow editing the state engine of a dialogue manager as a flow chart diagram.

7.10.1 "Choose 1. 2. 3. or 4. for an operator"

Question-answer dialogues are used in robots and telecom natural language systems. Typically a user is given a choice of menu points. (Spiliotopoulos *et al*., 2001) is a typical example how question driven dialogues are now being applied to robots, which interrogate their users. There is an argument that these systems work, because the human user has to adopt to the systems needs, but if this is true, why do most people choose 4 for an operator? Dean (2008) showed in a study titled "What's wrong with IVR self-service" that speech recognition in telephone applications is introduced to the benefit of the company rather than the user and that users prefer human operators. This possibly has implications for the social acceptance of speech recognition robots.

In a real human-to-human teaching scenario, however, there is no interrogation of the teacher in the corpus, there are however clarification questions after an explanation from the teacher. The teacher has the initiative in the dialogue, not the learner. The teacher chooses the topic and explains freely. Usually the student has a chance to interrogate the teacher at some point if questions arise. These student questions are usually only few and near the end of the teacher's explanation. Therefore the design principle must be:

When the teacher is teaching a task, the robot has to listen like a student.

The state engine of the dialogue is therefore a passive one, whereby states are changed by teacher utterances. The robot will only reply with "ok" to the teacher's instructions and otherwise say nothing. When after multi-modal unification a question arises from

the instruction, the robot will ask the question. After the question has been answered by the teacher it goes back into the mode with passive replies of "ok".

Even the robot usually does not have the initiative it still needs a dialogue model for understanding instructions. A dialogue state vector is used for this purpose.

Dialogue State Vector:

```
[MODE , PHASE , TURN , ISSUE]
```

7.10.2 Issue Stack

(Kruijf *et al*., 2008) argues that robots do not fully understand the environment they are situated in. At different stages of its reasoning the robot can become aware of missing information. Frame-based reasoning provides the ideal basis for this problem, since missing information simply means unfilled slots in a rule-frame instruction. Since more than one of these unfilled slots can appear, the questions to the users are put on a stack. A "issues raised stack" has also been suggested by (Lemon *et al*., 2001) in the WITAS dialogue system.

```
09.xml/teacher/2318-2396: "ok so if you cant go i mean if you cant capture a card then
you still have to lay one down you always have to lay a card down"
09.xml/student/2402-2413: "what from the main pack"
09.xml/teacher/2410-2439: "no from your hand of three"
09.xml/student/2443-2457: "where do i lay it to"
09.xml/teacher/2452-2474: "onto the table"
09.xml/student/2472-2481: "ok"
```

The ISSUE state in the dialogue state vector can go through the following states:

none → raise_question → wait_answer → none

As described earlier, questions can arise from missing information in rule frames. These questions are missing or ambiguous parameters in rule-frame instructions. A table below shows how these parameters are connected to questions to the teacher.

QUESTIONS TO THE USER

primitive	parameter	current state	text for text-to-speech engine (TTS)
move	dest-loc	unknown	'where do the cards go?'
move	source-loc	unknown	'where should i take the cards from?'
move	n	unknown	'how many cards would you like me to move?'
turn	n	unknown	many cards would you like me to turn over?'
turn	source-loc	unknown	'where are the cards that i should turn?'

Table 7-8: Questions to the user. Questions that the robot can ask in order to clarify information in a rule frame.

7.11 Summary on Knowledge Representation

This Chapter showed how natural language instructions, that have been converted through a grammar, can be reasoned with. The approach uses frame-based reasoning, embedding all knowledge into a structured knowledge base. Every instruction is part of a ruleframe that sets the context. These frames then become state transition rules so that the robot can plan and predict the consequences of its own actions. It was shown that missing information, that can be discovered through ambiguity or incomplete rule-frame instructions can be dealt easily discovered and requested from the user. In the next chapter, the framework will be put to the test.

8 Test and Evaluation

8.1 Test and Evaluation in Corpus-Based Robotics

The Corpus-centred approach to robot design, introduced as Corpus-Based Robotics, involves an experiment to collect a corpus at the beginning of the project, labelled in this chapter as E1. The robot is designed and implemented based on the corpus. This corpus collection experiment provides a rich source of data to carry out tests and evaluation. If the corpus-based design has been successfully applied, the robot should perform well when tested with the corpus. In fact, if human error in the task explanations is eliminated, the robot should recognise every task explanation successfully. It is an uncompromising test method of the implementation..

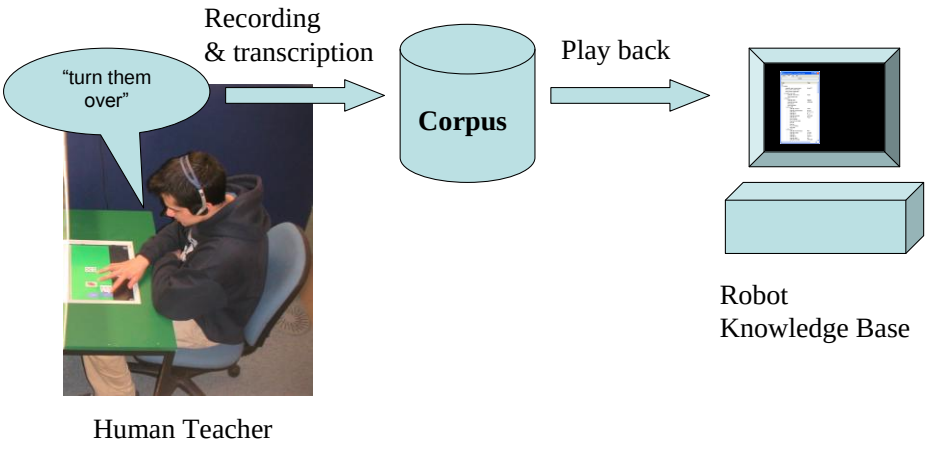


Figure 8-1: Using the corpus for testing: A form of test and evaluation is to play back the recorded teacher voice and actions to the robot, in this case a software agent.

Besides the experiments with recorded data, experiments with live (online) communication between the robot and a human teacher were conducted. These are the experiments labelled E4.1 and E4.2. . Before going into detail about the experiments, lets lay out the MIBL system and how it can be analysed.

8.2 Error Categories

There are many ways to measure a system's performance. In the case of testing MIBL it is of interest to make sure that *the robot learns and executes the instruction correctly.* This can be tested for every instruction the teacher gives. Every attempt of the teacher is indicated with <attempt> in the transcription for analysis. An attempt is defined as the teacher trying to say a game-rule to the robot in a single utterance. An attempt usually consists of a single utterance translated by a single primitive.

If there was no error and the rule was learned correctly the attempt is accompanied with the tag <error_none> in the transcription. If this is not the case, an "error" has occurred along the way. These errors can be put into categories according to the stage where they have occurred. The result shows where the system needs improvement and further research. Errors can cause a chain reaction of further errors, therefore the error of interest is the *first fatal-error* when following the information from the teacher through the system. The table 8-1 shows all error tags used for analysing experiments E4.1 and E4.2 on human-robot communication.

TABLE WITH TYPES OF ERRORS

XML-Tag	Level	Description
<error_ti>	Human	Error in the Teacher's instruction
<error_tgiveup>	Human	Teacher gives up with teaching instruction
<error_tdm>	Human	Wrong dialogue move of teacher
<error_se>	Recognition	Speech Recognition fails to recognise the utterance, eventhough the utterance is in the grammar and the HMM is therefore trained for it.
<error_ge>	Recognition	Gesture Recognition fails
<error_oosg>	Categorisation	Utterance not in the Speech Grammar (Out of Grammar Error)
<error_oogg>	Categorisation	Gesture not in Gesture Grammar, in other words, grouping of gestures is not correct (Out of Grammar Error)
<error_mmlink>	Categorisation	Wrong matching and linking between speech and gesture
<error_unif>	Categorisation	Wrong decision in unification or failed to unify primitive parameters
<error_dm>	Reasoning	Wrong dialogue move of robot
<error_ana>	Reasoning	Wrong decision in anaphora resolution or anaphora resolution failed
<error_kb>	Reasoning	Incorrectly stored instruction, for example in the wrong context
<error_exec>	Execution	Failure to execute instruction
<error_none>	-	Instruction had no error
<attempt>	-	attempt by the teacher to teach a game rule. This attempt usually consists of a single utterance containing a single primitive. Every attempt ends with an error-category or error_none. Number of attempts divided by number of error_none tags gives the success rate.

Table 8-1: List of types of Errors

In IBL, the error analysis was carried out in a similar fashion. The errors types were split into the categories Human Error, Speech Recognition, Semantic analysis, Functional Limitations and Execution problems. The fatal error per instruction was categorised. To better understand the information flow from the human speech through speech recognition, categorisation mechanisms such as multi-modal integration through to reasoning and execution, a diagram is given in figure 8-2.

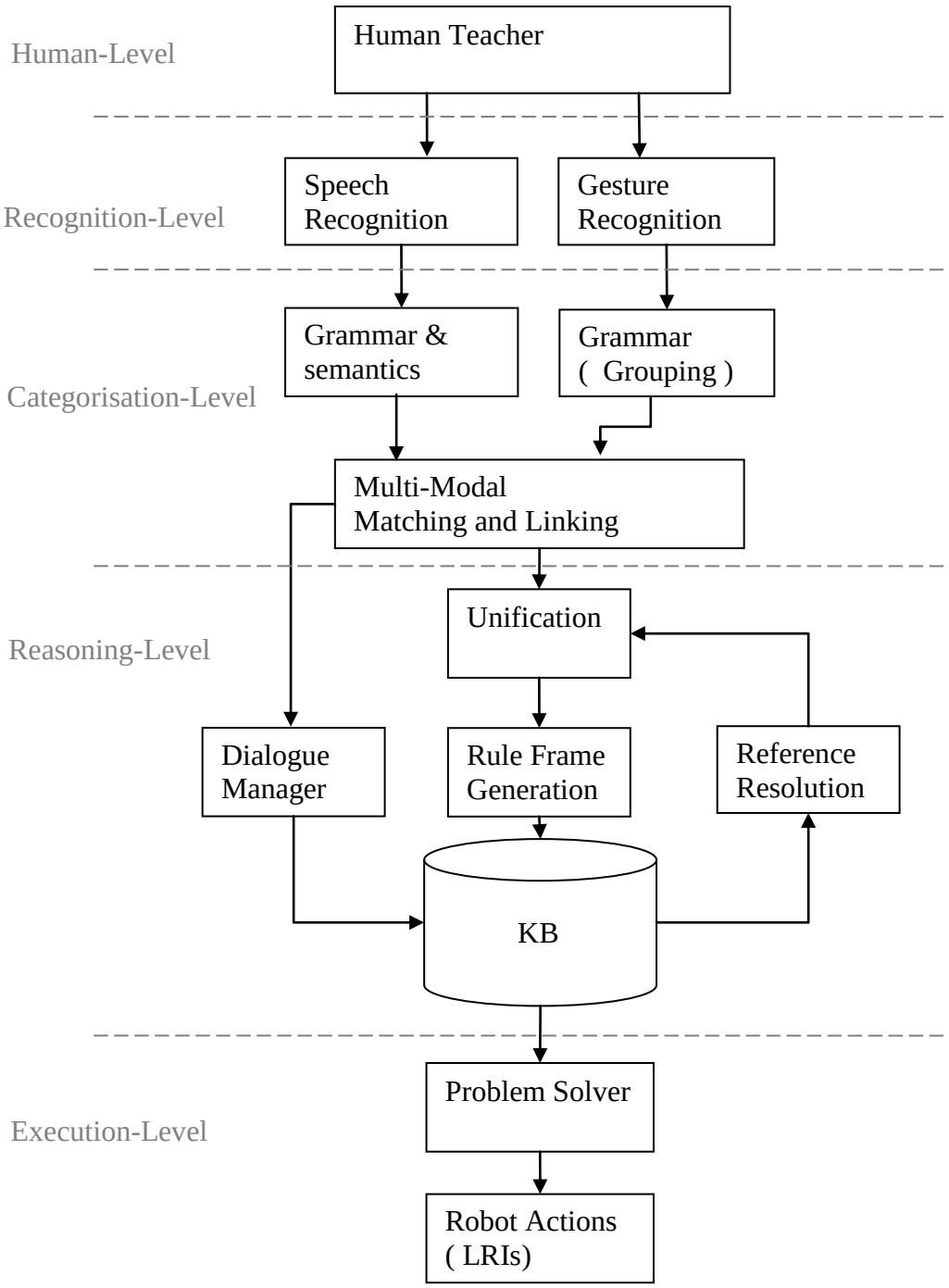


Figure 8-2: Overview of Levels in the MIBL system. These levels have been used to categorise the first fatal error of an instruction that the teacher explains. Information flows from top to bottom.

8.3 Overview of Experiments

The following shows a comprehensive list of experiments that have been carried out:

E1 Corpus collection

transcription of 35322 words and 1136 unique words

3827 utterances, 7411 gestures

(result: corpus available for research)

E2.1 Time-Based Multi-Modal Integration Algorithm test on corpus

(result: 100% assigned, 78% correct pairings , on data set-1)

E2.2 Time & Semantic Multi-Modal Integration Algorithm test on corpus

(result: 89% assigned, 100% correct pairings, on data set-1)

E3.1 System test of dealing phase by playing back from the corpus in text form

(result: learned correct instructions on set-1)

E3.2 System test of pair-rule by playing back from the corpus in text form

(result: learned 16 out 19 times the correct instructions on data set-1 + set-2)

E4.1 Deployment Pilot for Full System test with people

transcription of 745 words and 111 unique words,

190 utterances, 87 gestures

new knowledge to control experiment E4.2

E4.2 Full System test with people for Deployment

transcription of 119 new grammar rules, 3046 words added to the corpus,

300 unique words, 493 utterances, 201 gestures

Success rate per game rule:

pairrule 3 %

cardworth rule 29.5 %

cardexist 14.3 %

dealing 19.4 %

8.4 Testing Completeness in Corpus collection (E1)

The corpus collection experiment was described in detail in chapter 3. The photo figure 8-3 below shows again the setup with two people, one teaching the card game to the other.

Figure 8-3: Experimental Setup during Corpus Collection. Teacher and Student can both interact with a shared view of a virtual playing table. They are separated by a screen so that all gestures and action information goes through touch screen interaction. Servers for recording sound and touch screen are in the background.

One of the challenges in the corpus collection process is to know when to stop collecting. How many subjects need to be interviewed in order to cover the domain or at least be able to bootstrap a conversational robot for further collecting? This depends on the size of the domain. The size of the domain is a limiting factor in corpus-based robotics. Typically an artificially intelligent system can reason in a well defined world with limited concepts, but fails to function when too many new concepts are combined. Therefore the question is: how large is the domain of the MIBL project, i.e. the vocabulary and primitives of the Scopa card game. In order to get an idea of the size, a graph can be created that shows how often new, unknown words occur. See figure 8-4.

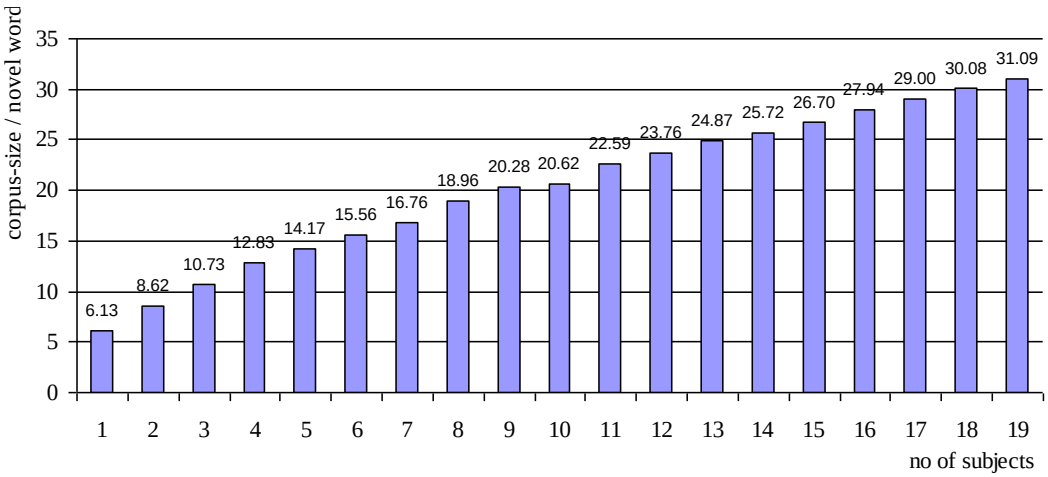


Figure 8-4: Novel words: With the growing size of the corpus, less novel words are discovered. The ratio corpus-size per novel-word is shown in the figure for **human-human corpus, experiment E1**. With an increasing number of subjects (corpus-size) more words go by until another novel word is discovered. A random subset of subjects is selected to create this graph, for example the average of any 1 of the 19 dialogues is taken create the first bar. The first bar shows approx. 6.13 which means that a novel word occurs every 6.13 words on average if the corpus consists only of the transcript of one subject.

After collecting dialogues, the period until a novel word is discovered has risen to the rate of 31 words. The inverse of the period is the frequency, whereby the axis is not time but the number of words "read" and stored in the corpus. The inverse (1/T) of the diagram above would show reduction in frequency of novel words, the more words are in the corpus.

The acceptable rate for stopping to expand (collect) the corpus is difficult to determine, however the graph 8-4 never goes to infinity since it slope almost levels towards the end of the graph. Or inverse the frequency of novel words never goes to 0. This means that there will always be new words discovered with the expansion of the corpus. This is a known phenomena in linguistics. A domain is never closed and there is always some new words discovered with further dialogues. It makes sense to keep collecting new vocabulary until the slope levels. From this point the maximum performance is reached in the domain for a given system. This process could be described as "bootstrapping".

Knowing there will be novel words which potentially cause problems to the speech recognition and understanding should be taken into account in the dialogue management so that the robot can react if a novel word occurred. In the case of MIBL the robot will reject the utterance with sentences like "I could not understand what you are saying". To further decrease the frequency of novel words, the user could be guided by the robot in what the robot understands. Therefore in MIBL, the robot repeats what the user said if the recognition probability is low, i.e. a novel word could potentially be in the utterance.

8.5 System test of dealing rule by playback from corpus in text form (E3.1)

In order to confirm that the system described in earlier chapters performs correctly (learning a rule as the teacher intended), the data of the corpus can be played back to the robot. This test is about testing the "learning" capability of the robot. The teacher's voice and touch-screen data is fed into the robot (software agent). In two experiments, the explanations of dealing of cards and the explanation of the pairing-rule are played back. The robot has a chance to ask questions during this learning phase. Since the playback of the corpus-recording is fixed and does not contain the answers, the operator pauses the experiment to answer questions of the robot manually. That the robot asks questions in different places that the human student, shows that the reasoning is not equivalent. The robot takes a more conservative approach and asks questions as soon as there is any room for uncertainty, while humans don't.

After a single rule explanation the robot is instructed to play. At this point the robot will start its problem solver to apply the learned rule. A printout of the rule-frames quickly reveals any problems during development. The corpus has been split into half named data set-1 and data set-2 to reduce the workload. In the first experiment, called E3.1, 10 dialogues (of our set-1) where played back to the robot, and the robot successfully learned the dealing rule in the way the teacher explained it. Appendix A12 shows a printout of the rule frames. The robot learned from human instructions.

8.6 System test of pair-rule by playback from corpus in text form (E3.2)

Similar to experiment E3.1 the aim of the experiment E3.2 is to confirm that learning of human instructions from the corpus works. In this case not the dealing of cards but the pairing rule is investigated. The pairing of cards is a complex rule consisting of conditionals as well as a sequence of actions to take the matching cards of the table. The success of the experiments would prove at least that the instruction primitives fit together and can be found in the corpus to build up the pairing rule in the robots representation format.

In this second experiment E3.2, a total of 19 dialogues (data set-1 and set-2) from the corpus were investigated. The investigated part of the dialogues contain explanations of how to capture cards by pairing them together. This part was previously tagged (with corpus tagging from chapter 3.4). In 3 cases the explanation of the pairing rule by the teacher was so incomplete that the robot did not know what to do. The robot successfully learned and applied pairing rule in all 16 remaining teaching dialogues. The explanations of the same rule can result in a different set of instructions, since every teacher has his individual understanding of the rule. The LRIs (low-level robot instruction) are actions that the robot produces to take action. Due to the different situations that the robot was in and the individual understanding of the rule, the robot produced different LRIs in figure 8-2.

Some teachers would show the card from the hand first before capturing for example. Others may define the winning pile in a different place. In most cases the teacher did not explain the pairing rule completely when comparing to the original rules of the game. However the robot was able to learn and execute the rule in the way the teacher explained it.

Session	Success / Failure	Comment	resulting LRI
03	S		move(C/QQ,+table,+hand1)
04	S		move(S/QQ,+hand2,+table)
05	S		move(S/QQ,+hand2,+side1)
06	S		move(S/QQ,+hand2,+temp2)
07	S		move(S/QQ,+hand2,+temp2), move(C/03,+hand2,+temp2)
08	S		move(C/QQ,+table,+temp2)
09	F	missing ifloc	
10	F	teacher does not explain pairing rule	
11	S		move(C/QQ,+table,+side2)
12	S		move(S/QQ,+hand2,+temp2)
13	F	teacher does not explain the rule completely	
14	S		move(S/QQ,+hand2,+temp2)
15	S	but teacher does not mention ifcond	move(C/JJ,+table,+hand2)
16	S	but unification assumes wrong source location	move(S/QQ,+hand2,+hand2)
17	S		move(S/QQ,+hand2,+temp2), move(C/QQ,+table,+side2)
18	S		move(D/04,+temp1,+hand1), move(H/04,+temp1,+hand1)
19	S		move(C/07,+table,+side2)
20	S		
21	S		

Table 8-2: Test on corpus of pairing rule

The experiments E3.1 and E3.2 proved that the language primitives can be found in the corpus and when played back they build up the dealing and pairing rules in the robots inner representation.

8.7 Pilot for Full System test with people (E4.1)

What can we learn from tests with people? The purpose of the test of the robot with people has several reasons. First of all it gives insights to how people communicate with the robot. Furthermore it shows how a corpus-based system is deployed. The deployment will show how the system adapts as new grammar rules are added during deployment. In a typical scenario of first deployment the corpus of the system is expanded. In a commercial environment, it is common practice to deploy a natural language system with a small corpus and then expanded it, see Nuance Gram. Dev. (2005). Nuance already provides a set of call logging and tuning tools for this purpose in mind. Further rationale for adding new grammar rules during deployment is to adapt the interaction to actual field of deployment, since the differences between corpus collection and deployment of the product have an impact on the vocabulary and grammar rules. Therefore, after each subject has been invited to communicate with the robot, the dialogue will be transcribed and new grammar rules will be added to the corpus. The reasoning and multi-modal integration system however will remain unchanged.

It was decided to do a pilot to prepare for the full test with people in a partly "controlled experiment". A pilot test will show initial problems with the communications between human and robot and if any improvements on the system and setup are necessary before starting deployment experiment E4.2. A "positive control" is a procedure that is very similar to the actual experimental test, but is known from previous experience to give a positive outcome. For instance, the previous experience is the corpus, were all subjects took 6 instructions to explain the dealing of cards (no complicated rules). If these 6 instructions can be reproduced with new subjects, the experimental setup and environment is right. New primitives were not expected to occur, which makes the semantics controlled and the outcome a "positive control".

For the grammar this is already an actual experimental test, a "not controlled environment", since new subjects will use new words and grammar that the robot does not know. The 6 instruction primitives for completing the dealing are shown in figure 8-5. Often the last two instructions 5 and 6 are regarded as start of the game, because the person picks up the cards in front of the him/her to look at them. Then only the first 4 are produced by the teacher.

```
"you have to deal three cards for each player"
 1.   move=ns-cardname-ns,03,+table+stock,+temp1
 2.   loopindicator=each

"place four cards in the middle of the table face up"
 3.   move ns-cardname-ns,04,+table+stock,+table
 4.   turn=ddd-cardname-+table,?,up

"drag the cards into your area and turn them over"
(missing, start of the game )
 5.   move=ddd-cardname-ns,?,?,+hand2 : imitate=now
 6.   turn=them-?-ns,?,?
```

Figure 8-5: 6 instructions primitives of the dealing phase in the format outputted from the grammar. Transcript of sub01try01.xml

8.7.1 Dialogue Management Issues and Solutions

Speech recognition is a hard problem, since speech recognition software is not achieving 100% recognition. This has implications for the dialogue between a speech recognition system and a human user. It is like speaking to person hard of hearing or a person who's English is not very good. In fact, subject 04 from the pilot experiment went closer to the microphone and spoke louder when repeating an utterance, because she believed the robot is hard of hearing. From the IBL project, it was found that people speak differently to a natural-language robot than to another person. The robot frequently requests the user to repeat what he or she said, because of bad speech recognition performance. However, the corpus was not recorded with persons that constantly ask for repeating the sentence. Therefore the dialogue structure with people talking to a robot is different to that of the corpus. Final report to the EPSRC about IBL (Bugmann 2003) suggests that the user can adapt to the robot's dialog and vocabulary, if the robot guides the user. The MIBL dialogue manager, like the IBL dialogue manager, will ask the user "did you say XYZ" if the speech recognition is unsure. This clarification process is better than just saying "can you repeat that please?". Repeating what the speech recognition understood provides feedback of what vocabulary and sentence structures the robot can understand. This feedback guides the user. Unfortunately this can be annoying to the user. Without this guidance, people would

simplify to a telegraphic style if the robot does not understand (Bugmann 2003). Communication would break down, since this style of telegraphic phrases is not in the corpus. Speech recognition should not be confused with natural language interpretation/understanding. The clarification process, which asks "did you say XYZ" comes after speech recognition, but before interpretation, which means that this dialogue has to be passed first before the semantics of the utterance get passed to the dialogue-manager and the knowledge base.

The clarification question by the robot, to some extend, interrupts the flow of the explanation of the teacher, especially in the case where the teacher has to repeat the sentence. This can be a problem simultaneously actions are carried out by the teacher for demonstration. Usually the demonstration is only carried out once, and not repeated during clarification. This has consequences for multi-modal integration, which relies on timing. As a solution, the timing of the user's first attempt to say the utterance is frozen and passed with the semantics to the dialogue-manager and unify-learn-mechanism. This way multi-modal integration timing is preserved. The user's first attempt to make his intentions known to the robot is the crucial one for multi-modal integration.

8.7.2 Procedure of pilot experiment

The instructions to the subjects can be found in appendix A2 and appendix A3.

4 subjects have been invited to take part in the pilot. Every subject had two tries to teach the robot. This small number is justified, since it is a pilot experiment. A set of paper strips with card game rules written on them is placed in front of the subjects, upside down. The subjects were instructed to take a paper strip. They studied the paper and had to give it back so they remembered the rules. In fact in the pilot all paper strips contained the same text, shown in figure 8-6. The conductor of the experiment tried to create an illusion that he genuinely didn't know the rules on these strips.

```
------------------------------------------------------------------------
This is a two player game.

Dealing:

deal 3 cards to each player

then deal 4 cards, face up, into the middle

                                                                  RS 203
------------------------------------------------------------------------
```

Figure 8-6: Paper strip with card game rule for the pilot test

After their attention was distracted from the rules by explaining the touch screen and the experimental setup, the subjects were asked to explain the rule to the experimenter, step by step. This is to clarify in the subjects mind how to teach the rules. During the whole experiment, the person running the experiment was not allowed to say any card game instruction to the subjects, unless they did not understand what was written on the piece of paper with the rules.

After it was assured that the subjects understood the rules they were allowed to explain it to the robot. The robot first says "could you explain the game to me please ?". The subjects went on to communicate with the robot until they have explained the rules and felt the robot understood. Then the experiment was stopped.

8.7.3 Findings, problems and changes from the Pilot Test:

1. The subjects did not believe that the experimenter didn't know the rule in advance and therefore their effort when explaining the rule to me was not instruction by instruction. This was corrected by reminding the subjects.
2. The subjects did not use 6 instructions like in the corpus because it did not occur to them that they have to take the cards into their hand and look at them in order to start playing. This was because they were only instructed to deal the cards and then stop. All produced the 4 dealing instructions from figure 8-5. This will not be a problem in the next experiment (E4.2) because it will include a game phase.
3. Two subjects first thought that the robot will move the card for them, while they are explaining. This is not what was found in the corpus. The corpus had all 19 teachers explaining the dealing phase by demonstrating (teacher doing the actions). The subjects do not feel they are talking to a normal playing partner.

One hypothesis could be the lack of embodiment or they think of the robot as a servant ?

4. One subject explained the dealing without demonstrating in the first try.
5. Subjects did not wait until the robot has finished speaking, before they answered. Particularly when the answer was “Yes” or “No”. A more clear busy icon was put in place, see the clock in figure 8-8. A real robot would show that its busy through its facial and body expressions.
6. The Recognition End-Point, which indicates the length of silence that is required after an utterance is regarded as finished has been increased from 0.6 to 1.4 seconds, to deal with hesitation. Users tend to hyper-articulate slightly (speak slowly with long breaks) if they think the robot does not understand.
7. Speech recognition errors and out-of-grammar errors made interaction difficult. To reduce the errors, 52 new grammar rules were added to the corpus with the use of the one-clause-one-primitive principle, see Appendix A13. In particular new grammar rules occurred in the dialogue management. More complex structures in the reply to robot questions were found. If the robot asked “how many cards would you like me to move?” the user can now say “three to the table” or related phrases, rather than just “three”.
8. 745 words added to the corpus, 111 unique (novel) vocabulary appeared which the robot didn’t know before.

8.8 Full System test with people (E4.2)

8.8.1 Procedure and Instructions

The pilot study and its analysis showed how the experimental setup can be improved. Taking into account the improvement and experiences, the full system test with people is conducted in a similar fashion to the Pilot test, i.e. subjects are invited. They draw from a pile of paper strips with rules printed on them. The exact instructions and procedure is in appendix A2 and appendix A3.

Role of the operator: During the explanation the subjects can get stuck because they can not find a phrase for the rule that the robot understands, then the operator (me) will encourage them to carry on with the next rule. The operator also can encourage to try that rule one more time with the robot. The operator can under no circumstances describe or use words of exactly what to say to the robot.

Figure 8-7: Experimental Setup for Final Test with subject sitting in front of the touch-screen, microphone and speakers. The subject is about to lean closer towards the microphone, because she is under the impression the robot does not understand.

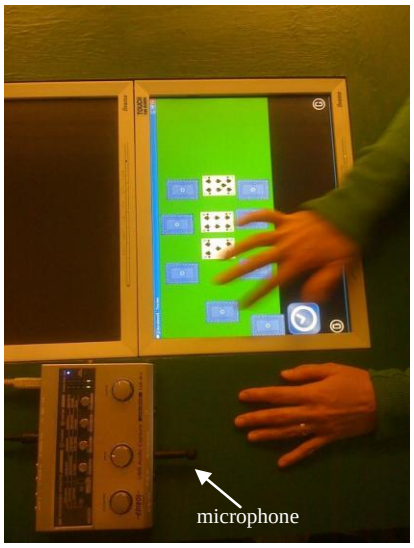


Figure 8-8: Table Setup for Final Test. External Sound Card with Interview Microphone to increase signal-to-noise ratio.

This time they are given the following rules to explain:

This is a two player game.

Dealing:

deal 3 cards to each player

then deal 4 cards, face up, into the middle

RS 1203

Playing:

a card on the table with the same value as a card in your hand are a pair.

you can take this pair to the side as a capture

RS 1697

---

the cards have their usual value

and the jack is worth 8 , queen is worth 9 and king is worth 10

ace is low

RS 1283

8,9 and 10 have been taken out from the deck

RS 4834

Figure 8-9: Paper strips with card game rules used for the full test

8.8.2 Results Overall

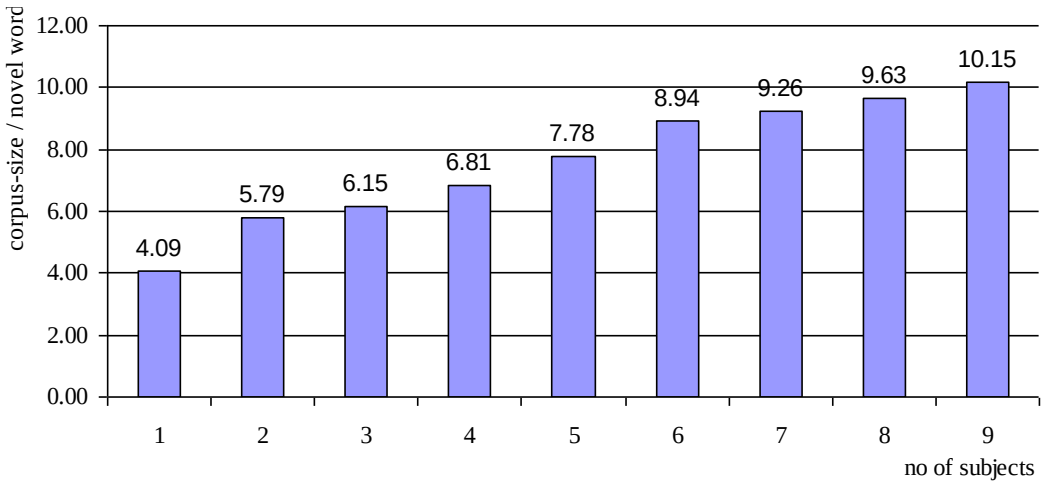


Figure 8-10: Novel words in final test:, experiment E4.2. With the growing size of the corpus, less novel words are discovered. The ratio corpus-size per novel-word is shown in the figure for **human-robot corpus, experiment E4.2**. With an increasing number of subjects (corpus-size) more words go by until another novel word is discovered. A random subset of subjects is selected to create this graph, for example the average of any 1 of the 9 dialogues is taken create the first bar. After adding 8 subjects to the corpus and comparing to the 9th, approximately every 10th word is novel (bar 9, value 10.15). The corpus from E1 was not included in this graph.

The graph 8-10 can be compared to figure 8-4, which also measured after how much words another novel word appeared. The corpus for E4.2 has 3046 words, which is considerable smaller than E1. When testing both together (not shown in graphs) the effect of adding E4.2 to E1 has hardly any impact on the corpus-size / novel-word ratio.

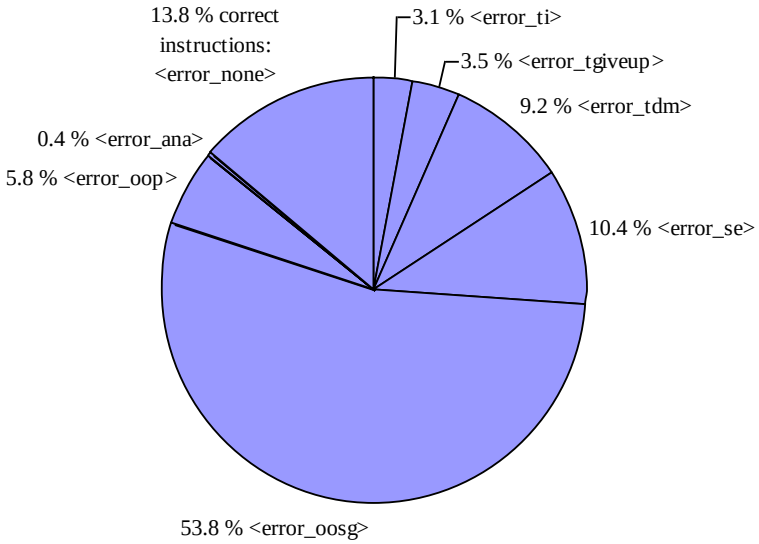


Figure 8-11: Performance of Final Experiment, no error in 13.8 % of attempts. Majority of errors 53.8 % come from category <error_oosg> (error out-of-speech grammar) which means that approximately every second utterance is not defined in the grammar and therefore the robot fails to recognise the attempt of the teacher to teach the instruction. This graphs shows the errors occurred over the whole deployment test of 9 sessions. The actual errors varied from session to session depending on the human subject and the progression in the robots knowledge of grammar rules.

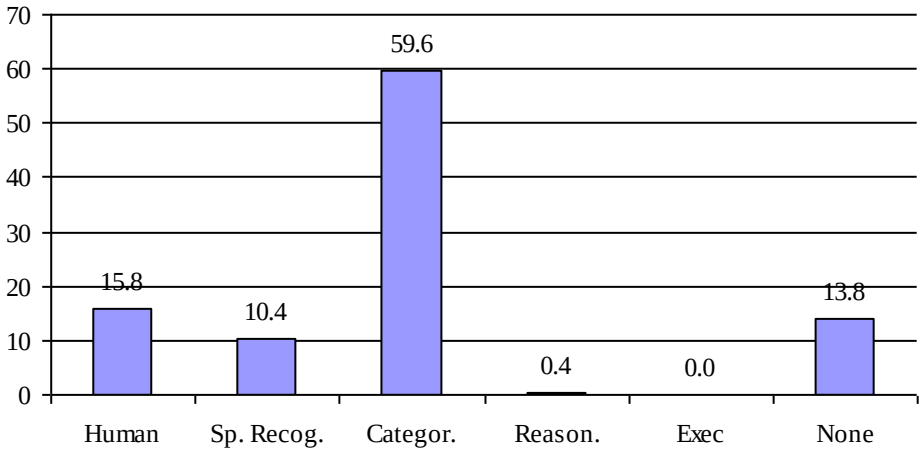


Figure 8-12: Errors split in categories: The errors shown in Figure 8-11, divided into categories from Figure 8-2. Categories from left to right: Human Error, Speech Recognition Error, Categorisation Error, Reasoning and Reference Resolution Error, Execution Error, No Error. For an explanation of the error categories, see table 8-1.

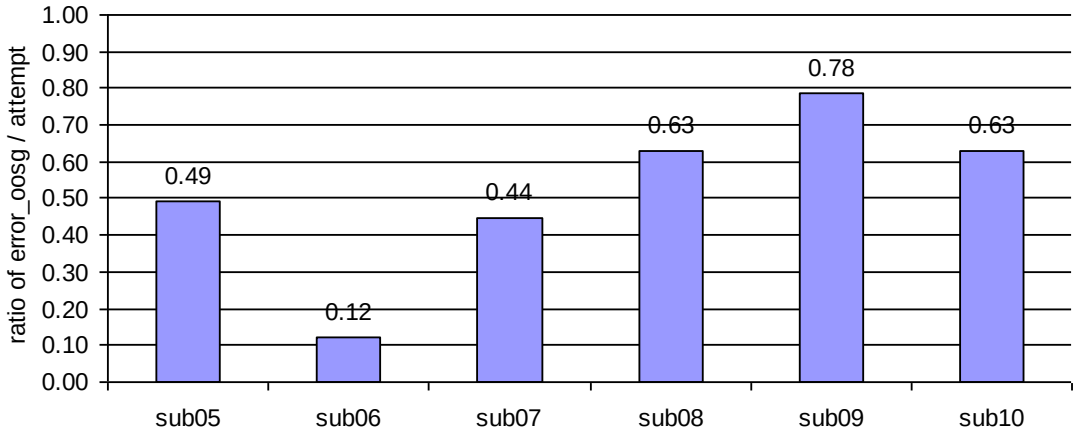


Figure 8-13: Ratio between error_oosg and no of attempts. A smaller number means less errors. After every subject new grammar rules are added that have caused the oosg-errors. There is no decrease in errors as more rules are covered. Through its randomness it seems that this graph measures the alignment of the subject with the robot rather than the influence of increasing corpus size.

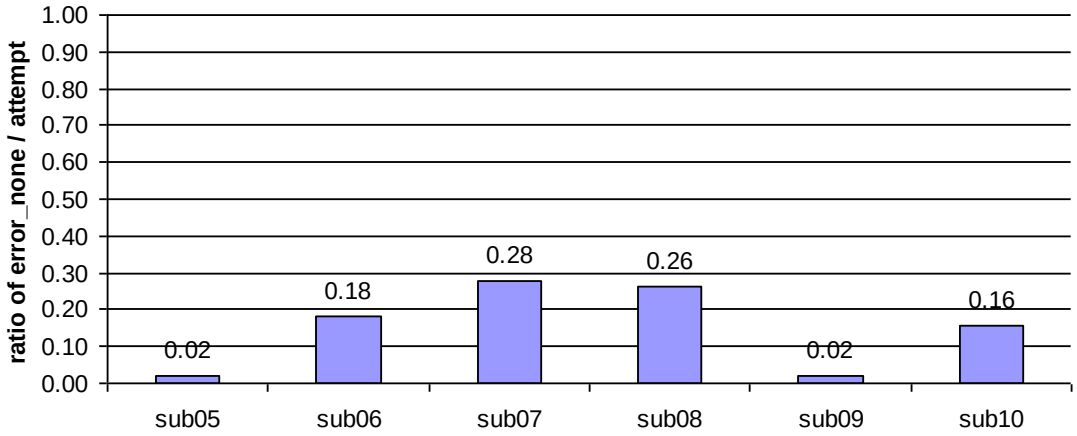


Figure 8-14: Success rate per subject:, ratio between error_none (success) and number of attempts. Sub05 1/55, Sub06 6/33 , Sub07 10/36 , Sub08 12/46 , Sub09 1/51 , Sub10 6/38 .

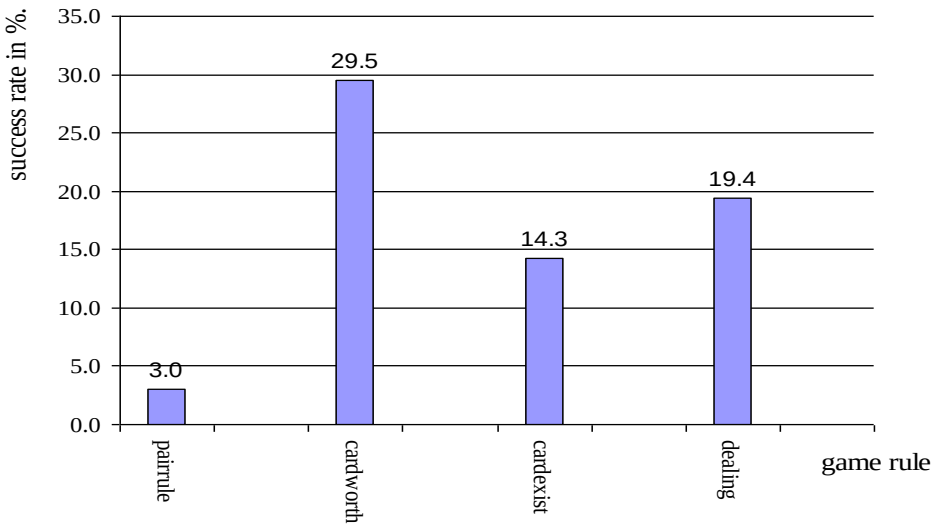


Figure 8-15: Success rate (<error_none>) per game rule. Every attempt (<attempt>) of the teacher to convey the rule is counted. If the attempt was successful, i.e. the robot understands the intention of the primitives without error, it is counted as success (shown in %). If anything goes wrong, i.e. robot error, teacher error, the attempt is counted as a failure. The rate is the total attempts divided by the successful ones. It is clear from this graph that some rules are easier to teach, for example how much points a card is worth (<cardworth>) is understood by the robot after approx. three attempts(29.5%) while the pairing of cards is a more complex rule and has many ways to be expressed, which caused unacceptable success rate of 3%.

Morphology such as singular and plural was not taken into account, and would be counted as separate words, i.e. “dog” “dogs” are counted as separate words.

8.8.3 Findings and Problems from the Final Test and Discussion

1. The experiment added 119 new grammar rules, 3046 words and 300 novel vocabulary to the corpus.
2. People did not use the touch screen as much as in the Human-to-Human corpus E1. Similarly to the pilot experiment there is a lack of flow in the dialogue because of the bad speech recognition performance and out of grammar errors 53.8 %. The repeated rejections of their utterances possibly deterred the subjects doing the actions while speaking compared to the human-to-human corpus. The reduction of Multi-modal interaction to the single modality speech was not an expected finding. Hypothetically, the modality could also have been gesture instead. However only subject 06 (sub06try1.xml) went to do more actions and shorted his sentences to "can you make a pair?". Everyone else tended to engage with clarification dialogue and reduced gestures.
3. This time the subjects completed the dealing phase, but failing to make the robot pick up its own cards, mainly because of out-of-grammar errors. The fact that the robot did not pick up its cards made the users suspicious of its capabilities another factor is that lack of embodiment. I.e. it does not have a visible arm and hand. The robot without cards in his hands leads to confusion on how to carry on to the pairing rule explanation. Picking up cards is often an implicit instruction. It is coded as such by adding the "imitate=now" primitive to the grammar if the teacher talks about picking up his cards. Teachers don't say "I pick up my cards, please pick up yours too" They expect imitation when they pick up theirs, or the other way round instruct the robot to pick up his and pick up theirs without telling.

Traditionally a performance test of the robot would have been carried out without adding grammar rules. What would hypothetically been the outcome of such a test that would not add grammar rules after each session ? Certainly the out-of-grammar errors for instance would have been at least as high as now. The logical conclusion and recommendation at the end would have been to add more grammar rules to cover the domain and therefore reduce out-of-grammar errors. This deployment test however showed that this would not have worked. Graph 8-13 does not go down with the progression over more subjects. The deployment test is already a step ahead of the usual

static analysis and shows an interesting finding, namely the out-of-grammar errors can not be reduced linearly by just adding more grammar rules.

8.8.3.1 Out-of-Grammar Errors

Out-of-Speech-Grammar errors:

As seen in graph 8-13, the rate of Out-of-Speech-Grammar errors < error_oosg> is not decreasing over the progression of more subjects. Also the success rate in graph 8-14 is not increasing. It can be hypothesised that the adding of new grammar rules does not affect the success rate at this size of the corpus. It would affect it, however, if the corpus is very small of course, since without a minimum of grammar rules there is no success at all.

This is a clear indicator that these instructions have *a large variety of being expressed in language*. Here lies a clear limitation of the corpus-based approach or indeed any natural language interface. The rate of errors must decrease to a user-bearable rate before a system can be said usable in practice. This important finding first of all limits the application of the corpus-based approach to instruction-domains that have a limited expressions/size. It will probably limit any other approach (not only corpus-based) that requires grammar-to-robot function mapping. The limit is the cost implication of mapping what hundreds of users said, rather than the concept.

Three recommendations can be made from these results specifically regarding domain size:

1. Alignment of the speaker and the robots grammar by replying with utterances that guide the human to use the right sentence structure and vocabulary.
2. A pilot study needs to be carried out on a domain. The pilot study measures the OOSG / instruction rate. This will show if the corpus-based approach is feasible for the domain. If not, a more restrictive dialogue may be necessary which is more stressful to the user on the other hand. Some domains are so large that they have to be split into sub-domains. A robot working in a department store is a typical example, each department would be a sub-domain to keep implementation feasible.

3. Further research is required into natural language understanding to explore more cost-effective ways of mapping complex language grammar to semantics and robot primitives.

It seems that corpus-based linguistics has suffered from the same problem see (Leidner 2003): “Such training corpora are typically expensive or\virtually non-existent (data resource bottleneck)...leads to unacceptable accuracy”

The IBL domain for example seems to be much smaller than the MIBL domain. Further research is needed to investigate indicators of a domain size. The out-of-grammar errors of IBL are difficult to compare since it suffered from a problem with grammar design.
Lets expand on recommendation one from above. The final report to the EPSRC about IBL (Bugmann 2003) suggests that the user can adapt to the robot’s dialog and vocabulary, if the robot guides the user. (Garrod and Pickering, 2004) talk of an alignment process between the two conversation partners. In this alignment linguistic representations are aligned so that both come to an understanding. The simplest version of this alignment is implemented in MIBL as the robot repeats what it understood using the words that are in the grammar with “did you say XYZ”. However there is much more potential for doing clever alignment, not only with vocabulary and grammar but also in semantics. What does the teacher understand by “on the table” or the robot may be two different things. By exploiting alignment the oosg-errors can be reduced. The Nuance Gram. Dev. (2005) mentions that 5%-20% of out-of-grammar typically occur, whereby the Nuance guide book assumes a strict interrogative dialogue management. In fact it suggest, one should start with designing the dialogue and then the grammar. This is not the way forward but it shows that the dialogue management influences the out-of-grammar errors. The problems of menu driven restricted dialogue control, as it is used in industry today are compared to the MIBL approach with free speaking in table 8-3. Is a mixture of both ways the answer ? This may be answered in future research.

Control of Dialogue	Human Teacher	vs.	Robotic Student
Properties	Free speaking of the human, the robot only asks questions sometimes. The robot lets the user change context any time.		Robot asks question, human only allowed to answer in a from the robot suggested form, i.e. “yes”,” no”, “one”, “two”. Menu driven, like automatic telephony system. Interrogative .
Advantages	- emulates the traditional dialogue between teacher and student, which is natural for teaching scenario		- alignment between robot and human is better, which means there are few speech recognition and out-of-grammar errors.
Disadvantages	- as seen in MIBL the free choice of vocabulary and sentence structure causes a large amount of out-of-grammar errors. It is hard to control them if the robot is not driving the user to alignment.		- the alignment is forced by the robot-student, effectively making the student in charge of the teaching flow and content. This leads to frustration by the human-teacher who can not continue in the way he wants.

Table 8-3: Human vs. Robot Dialogue control. Effect on Alignment

Combinatorial explosion of Grammar rules:

Novel vocabulary is not the only obstacle, the large amount of possible combination of vocabulary, i.e. the grammar is a further limitation. With novel words new possible combinations are introduced which, cause in the worst case, an exponential increase of grammar rules. Key word spotting, or SLM[11] grammars for speech recognition suffer from this problem. With the use of word classes and the one-clause-one-primitive principal the combinations are limited. This limit keeps a lid on the exponential growth problem that for example a keyword spotting grammar would suffer from. Exponential growth is bad for speech recognition. It reduces the probability of finding the correct pathway through the Hidden Markov model (in NUANCE called “confidence”). Often the primitive is recognised correctly, but parameters were erroneous because of the lower probability to get word classes right. If the number of possibilities of expressing an instruction is large, it is necessary to collect a large amount of samples for the one-clause-one-primitive method. Generally it was noted that complex instructions have a larger variety of being expressed. For instance, the pairrule in Figure 8-13 shows a

[11] Statistical Language Modeling

success rate of only 3% because the pairing rule has the largest variety of being expressed.

8.8.3.2 Speech Recognition errors

Speech-recognition errors are marked <error_se> and appear if despite an utterance being defined in the grammar, it is not recognised. 10.4% of errors where due to speech recognition, see 8-11 and 8-12. Nuance claims that the new version Dragon Naturally Speaking 9 has a 20% higher recognition rate than the previous version 8. Assuming this statement is true, the error rate can be reduced further by using the latest speech recognition software. Good audio equipment also has an influence.

8.8.3.3 Human Error

Human error shown in figure 8-12 as 15.8 % consists of 3.1 % <error_ti> (teacher instruction errors), 3.5 % <error_tigiveup> (teacher gave up explaining deliberately) and 9.2 % <error_tdm> (teacher dialogue move error).

Even though all subjects have been tested if they can explain the rules correctly, 3.1 % gave wrong instructions. They made mistakes in their verbal expressions, without noticing. Some of these <error_ti> may come through a lack of concentration or accuracy in the English.

The <error_tgiveup> was due to frustration of the teacher, often after many failed attempts of saying an expression without success.

The <error_tdm> comes from a mismatch in the dialogue, i.e. the robot asks a question, but the teacher does not answer and instead talks about something else. The very simple dialogue manager from MIBL was not able to handle this. Sometimes the error also occurred when the robot asks a question about a previous instruction on the stack, and the teacher already moved on to the next instruction. This caused confusion in both, the teacher and robot. The human teachers were instructed to say “forget it” or similar expressions if they felt the robot was confused.

9 Conclusions and Future Work

9.1 Achievements

In Chapter 1, the aim of the work has been set out as a contribution to knowledge in the field of human-robot communication. More specifically how to convert unconstrained multimodal instructions (spoken natural language + gestures/actions) into a knowledge representation usable for robot reasoning and acting from Chapter 1.1 .

The thesis has shown how to work towards this aim by introducing multi-modal integration algorithms in chapter 5. Particular attention was paid to natural instructions from human-to-human, and the attempt to make algorithms for a robot to capture and integrate these. These natural instructions can not only consist of sequences, like in an assembly task, but also of conditionals which occur in rules. It was shown that a time window for gesture and utterance overlap exists. In combination with semantic matching and nearest neighbour matching a match between the right gestures and utterances was made possible. The results have been quantified in previous chapters 5.3.2 , 8.5, 8.6 .

The work has also shown that contributions have been made in the area of converting actions into usable knowledge for a robot. The finding of primitives (Chapter 3.5, 6.1) and generating a grammar with the use of Corpus-Based Robotics (Figure 1-3) have been shown to be a useful method in order to achieve this aim. The results have been quantified in Chapter 8.

Finally a further aim was to enable a robot to reason and act upon this knowledge gained from human instructors. It was shown in Chapter 7, a combination of frame-based reasoning and an ontology of the robots world enabled reasoning. More specifically, rule-frames and later state transition rules were created from human instructions, which hold the context and actions that the robot has to carry out. These rule-frames provided the robot with a framework that allowed reasoning such as unification, reference resolution, action prediction and planning. Finally all results, shown in chapter 8 and 5.3.2 were critically analysed. These tests showed what happens in a deployment scenario. Interesting findings such as the influence of adding new vocabulary and grammar rules which did not reduce out-of-grammar errors, were demonstrated in the tests. The tests showed the points where corpus-based robotics needs improvement and further research.

9.2 Comment on the corpus-based Robotics approach

The corpus-based approach is a method to create a system that is able to understand instructions that are given at a high human-like level. This leaves the developers with the burden of trying to create very complex robot primitives. First of all it must be said that this is a good way of making researchers address hard real world problems. The corpus comes from end-users and is used for testing the final system, which is therefore rigorous and unforgiving.

However the corpus collection and transcription adds additional work compared with the traditional product development methods, where they are absent. This leads to an overall increase of labour and cost of the product. However, in theory, the product will match user requirements exactly and be able to communicate naturally which may justify the increased price. Furthermore a corpus-based robot will have a wider range of customers, since it could potentially be used by the elderly or by functionally illiterate people.

9.2.1 Human-to-Human vs. Human-to-Robot dialogues

It was observed that people speak differently to robots than to humans. This has caused problems in IBL and MIBL because the corpus has been based on human-to-human dialogues. In the future a wizard-of-oz approach should be taken during corpus collection, whereby the subject must be under the impression of talking to a robot, from the start. It might be necessary to imitate problems with speech recognition during corpus collection. The human to robot dialogues suffered from a too simple dialogue manager that could not guide the user well enough on what the robot can understand. By using alignment techniques, i.e. guiding the user in what expressions the robot understands, it may be possible to reduce out-of-grammar errors in future work.

9.3 Future Work

This paragraph shows possible future work on the MIBL project specifically.

- Comparison and integration of statistical learning algorithms for gesture recognition (from chapter 4.3 Advanced Gesture Recognition). This could improve accuracy in gesture recognition.
- The dialogue model is too rigid and cannot detect if the user decides not to answer a question. Much more can be done to make the dialogue better to keep the context between robot and teacher aligned.
- What is the role of apparent skill level in the dialogue? How to show capabilities of the robot to the user.
- Ask the subjects why they want the robot to do something that they usually would demonstrate themselves if a human would be their student.
- More clever dialogue management guides the user to use the right expressions. This needs to be exploited more and can significantly reduce the <error_oosg>.
- An interesting investigation could be to define a multi-modal grammar and modelling its recognition with HMM.
- Learning locations for gesture recognition from examples (grounding).

9.4 What is holding back user-programmable robots?

An aim set out in the introduction was to advance methods for producing a user-programmable robot for a specific domain. The work presented in this thesis has made progress by showing a method of multi-modal integration and a knowledge-representation scheme in the area of task learning.

Speech recognition is a major limitation and holding back the development of user programmable robots. The experiments have shown that 13.8% + 53.8% of errors is due to speech recognition and grammar problems. The rate is so high that it is not useful in practical applications. For the same reason we still use keyboards on our PCs. As (Lauria, 2007) correctly points out, speech interfaces still do not outperform keyboard based interfaces, for example the voice-dialling option on a mobile phone is hardly used, even it is built into many phones.

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