

COGNITIVE INTERACTIVE ROBOT LEARNING

BENJAMIN FONDONI



Department of Computing Science PhD Thesis, Umeå 2014

Cognitive Interactive Robot Learning

Benjamin Fonooni



PhD Thesis, December 2014 Department of Computing Science Umeå University Sweden Department of Computing Science Umeå University SE-901 87 Umeå, Sweden

fonooni@cs.umu.se

This work is protected by the Swedish Copyright Legislation (Act 1960:729) Copyright © 2014 by the authors Except Paper I, © 2012 SCITEPRESS Paper II, © 2013 IEEE Computer Society Press Paper III, © 2014 Elsevier B.V. Paper IV, © 2013 IEEE Computer Society Press Paper VI, © 2015 ACM Paper VII, © 2015 IEEE Computer Society Press

ISBN: 978-91-7601-189-8 ISSN: 0348-0542 UMINF: 14.23

Cover design by Omid Mohammadian. Back cover portrays an Achaemenid soldier carved on the walls of Persepolis.

Electronic version available at http://umu.diva-portal.org/ Printed by: Print & Media, Umeå University Umeå, Sweden 2014

Abstract

Building general purpose autonomous robots that suit a wide range of user-specified applications, requires a leap from today's task-specific machines to more flexible and general ones. To achieve this goal, one should move from traditional preprogrammed robots to learning robots that easily can acquire new skills. Learning from Demonstration (LfD) and Imitation Learning (IL), in which the robot learns by observing a human or robot tutor, are among the most popular learning techniques. Showing the robot how to perform a task is often more natural and intuitive than figuring out how to modify a complex control program. However, teaching robots new skills such that they can reproduce the acquired skills under any circumstances, on the right time and in an appropriate way, require good understanding of all challenges in the field.

Studies of imitation learning in humans and animals show that several cognitive abilities are engaged to learn new skills correctly. The most remarkable ones are the ability to direct attention to important aspects of demonstrations, and adapting observed actions to the agents own body. Moreover, a clear understanding of the demonstrator's intentions and an ability to generalize to new situations are essential. Once learning is accomplished, various stimuli may trigger the cognitive system to execute new skills that have become part of the robot's repertoire.

The goal of this thesis is to develop methods for learning from demonstration that mainly focus on understanding the tutor's intentions, and recognizing which elements of a demonstration need the robot's attention. An architecture containing required cognitive functions for learning and reproduction of high-level aspects of demonstrations is proposed. Several learning methods for directing the robot's attention and identifying relevant information are introduced. The architecture integrates motor actions with concepts, objects and environmental states to ensure correct reproduction of skills.

Another major contribution of this thesis is methods to resolve ambiguities in demonstrations where the tutor's intentions are not clearly expressed and several demonstrations are required to infer intentions correctly. The provided solution is inspired by human memory models and priming mechanisms that give the robot clues that increase the probability of inferring intentions correctly. In addition to robot learning, the developed techniques are applied to a shared control system based on visual servoing guided behaviors and priming mechanisms.

The architecture and learning methods are applied and evaluated in several real world scenarios that require clear understanding of intentions in the demonstrations. Finally, the developed learning methods are compared, and conditions where each of them has better applicability are discussed.

Sammanfattning

Att bygga autonoma robotar som passar ett stort antal olika användardefinierade applikationer kräver ett språng från dagens specialiserade maskiner till mer flexibla lösningar. För att nå detta mål, bör man övergå från traditionella förprogrammerade robotar till robotar som själva kan lära sig nya färdigheter. Learning from Demonstration (LfD) och Imitation Learning (IL), där roboten lär sig genom att observera en människa eller en annan robot, är bland de mest populära inlärningsteknikerna. Att visa roboten hur den ska utföra en uppgift är ofta mer naturligt och intuitivt än att modifiera ett komplicerat styrprogram. Men att lära robotar nya färdigheter så att de kan reproducera dem under nya yttre förhållanden, på rätt tid och på ett lämpligt sätt, kräver god förståelse för alla utmaningar inom området.

Studier av LfD och IL hos människor och djur visar att flera kognitiva förmågor är inblandade för att lära sig nya färdigheter på rätt sätt. De mest anmärkningsvärda är förmågan att rikta uppmärksamheten på de relevanta aspekterna i en demonstration, och förmågan att anpassa observerade rörelser till robotens egen kropp. Dessutom är det viktigt att ha en klar förståelse av lärarens avsikter, och att ha förmågan att kunna generalisera dem till nya situationer. När en inlärningsfas är slutförd kan stimuli trigga det kognitiva systemet att utföra de nya färdigheter som blivit en del av robotens repertoar.

Målet med denna avhandling är att utveckla metoder för LfD som huvudsakligen fokuserar på att förstå lärarens intentioner, och vilka delar av en demonstration som ska ha robotens uppmärksamhet. Den föreslagna arkitekturen innehåller de kognitiva funktioner som behövs för lärande och återgivning av högnivåaspekter av demonstrationer. Flera inlärningsmetoder för att rikta robotens uppmärksamhet och identifiera relevant information föreslås. Arkitekturen integrerar motorkommandon med begrepp, föremål och omgivningens tillstånd för att säkerställa korrekt återgivning av beteenden.

Ett annat huvudresultat i denna avhandling rör metoder för att lösa tvetydigheter i demonstrationer, där lärarens intentioner inte är klart uttryckta och flera demonstrationer är nödvändiga för att kunna förutsäga intentioner på ett korrekt sätt. De utvecklade lösningarna är inspirerade av modeller av människors minne, och en primingmekanism används för att ge roboten ledtrådar som kan öka sannolikheten för att intentioner förutsägs på ett korrekt sätt. De utvecklade teknikerna har, i tillägg till robotinlärning, använts i ett halvautomatiskt system (shared control) baserat på visuellt guidade beteenden och primingmekanismer. Arkitekturen och inlärningsteknikerna tillämpas och utvärderas i flera verkliga scenarion som kräver en tydlig förståelse av mänskliga intentioner i demonstrationerna. Slutligen jämförs de utvecklade inlärningsmetoderna, och deras applicerbarhet under olika förhållanden diskuteras.

Preface

This thesis presents techniques and cognitive architectures for Learning from Demonstration (LfD) and Imitation Learning (IL) challenges. High-level learning and reproduction of behaviors is discussed, and our contributions to the field are elaborated. The thesis is based on the following papers:

- Paper I: Benjamin Fonooni, Thomas Hellström and Lars-Erik Janlert. Learning high-level behaviors from demonstration through Semantic Networks, In proceedings of 4th International Conference on Agents and Artificial Intelligence (ICAART), Vilamoura, Portugal, pp. 419-426, 2012.
- Paper II: Benjamin Fonooni, Thomas Hellström and Lars-Erik Janlert. Towards Goal Based Architecture Design for Learning High-Level Representation of Behaviors from Demonstration, *IEEE International Multi-Disciplinary Con*ference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), San Diego, CA, USA, pp. 67-74, 2013.
- Paper III: Benjamin Fonooni, Aleksandar Jevtić, Thomas Hellström and Lars-Erik Janlert. Applying Ant Colony Optimization algorithms for High-Level Behavior Learning and Reproduction from Demonstrations, *Robotics and Au*tonomous Systems, 2014 (accepted).
- Paper IV: Alex Kozlov, Jeremi Gancet, Pierre Letier, Guido Schillaci, Verena V. Hafner, Benjamin Fonooni, Yashodhan Nevatia and Thomas Hellström. Development of a Search and Rescue field Robotic Assistant, *IEEE International Symposium on Safety, Security, and Rescue Robotics*, Linköping, Sweden, pp. 1-5, 2013.
- Paper V: Benjamin Fonooni, Thomas Hellström and Lars-Erik Janlert. Priming as a Means to Reduce Ambiguity in Learning from Demonstration, International Journal of Social Robotics, 2014 (submitted).
- Paper VI: Benjamin Fonooni and Thomas Hellström. On the Similarities Between Control Based and Behavior Based Visual Servoing, The 30th ACM / SIGAPP Symposium on Applied Computing (SAC), Salamanca, Spain, 2014 (accepted).
- Paper VII: Benjamin Fonooni and Thomas Hellström. Applying a Priming Mechanism for Intention Recognition in Shared Control, *IEEE International Multi*-

Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), Orlando, FL, USA, 2014 (accepted).

In addition to above papers, the following paper has been produced during the PhD studies:

• Benjamin Fonooni. Sequential Learning From Demonstration Based On Semantic Networks, Umeå's 15th Student Conference in Computing Science (USCCS), Umeå, Sweden, 2012.

This work was partly financed by the EU funded Initial Training Network (ITN) in the Marie-Curie People Programme (FP7): INTRO (INTeractive RObotics research network), grant agreement no.: 238486.

Acknowledgments

It would not have been possible to write this thesis without the help and support of many kind people. First, I offer my sincerest gratitude to my supervisor Thomas Hellström who has supported me throughout my PhD career with his inexhaustible patience and knowledge. He is not only a great supervisor who provides invaluable guidance, meticulous suggestions and astute criticism, but also a close friend who has always been there for me. Besides Thomas, I would like to thank my co-supervisor Lars-Erik Janlert for his encouragement and insightful comments especially on cognitive aspects of the thesis.

My sincere thanks to Erik Billing for his support and fruitful discussions especially on integrating PSL into my work, all of which were enlightening. I would like to show my greatest appreciation to Ola Ringdahl for his kindness in answering all my questions. I am very delighted to have Ahmad Ostovar as a friend, with whom I shared wonderful moments. I am also very lucky to have Peter Hohnloser as a friend, whose company is always a treat.

I wish to take the opportunity to extend my gratitude to everyone at the department of Computing Science for their cooperation, understanding, and support that make it a pleasant working environment. I would also like to express my appreciation to my fellow ESRs and other colleagues from the INTRO project for their support and friendship throughout the project. I am particularly grateful for the helpful assistance on Ant Colony Optimization given by Aleksandar Jevtić from Robosoft.

I would also like to express my deepest gratitude to my parents, Behnam and Hayedeh, for the inspiring education they provided me.

Lastly, and most importantly, I am grateful to my lovely wife Sepideh, who has been with me all the way, with her true love and patience although she went through tough times. Her endeavors to provide a peaceful and comforting atmosphere for my studies undoubtedly affected the final work.

Umeå, December 2014 Benjamin Fonooni

Contents

1	1 Introduction						
	1.1	Levels of Abstraction	2				
	1.2	Objectives	3				
	1.3	Thesis Outline	3				
2	Cha	allenges in Learning from Demonstration	5				
	2.1	Big Five	5				
		2.1.1 Who to Imitate	5				
		2.1.2 When to Imitate	6				
		2.1.3 What to Imitate	6				
		2.1.4 How to Imitate	6				
		2.1.5 How to Evaluate Successful Imitation	7				
	2.2	Other Challenges	7				
		2.2.1 Generalization	7				
		2.2.2 Sequence Learning	8				
		2.2.3 Learning Object Affordances	8				
9	Coo	mitive Analytication for Learning from Demonstration 1	1				
3	2 1	Poloted Work	1				
	0.1 2.0	Proposed Arabitatura	.т 6				
	3.2	2.2.1 Handware Setup	.0 7				
		2.2.2 Demonstration Unit	.1				
		3.2.2 refreeption Unit	0. 0				
		2.2.2.1 High Level Controllon	0. 0				
		3.2.3.1 High-Level Controller	0. 0				
		3.2.3.2 Low-Level Controller	.9 00				
		3.2.4 Output Unit	20 20				
4	Lea	rning High-Level Representation of Behaviors 2	1				
	4.1	Why Semantic Networks	!1				
	4.2	Learning Methods					
		4.2.1 Hebbian Learning 2	23				
		4.2.2 Novelty Detection	:4				
		4.2.3 Multiple Demonstrations	:4				
		4.2.4 Multiple Demonstrations With Ant Algorithms 2	:5				

CONTENTS

		4.2.5 Comparison of Methods	25							
	4.3	Generalization	26							
5	\mathbf{Am}	biguity in Demonstrations	29							
	5.1	Ambiguity	29							
	5.2	Priming	30							
	5.3	Priming to Resolve Ambiguity	31							
6	Sha	red Control	33							
	6.1	Shared Control for Learning from Demonstration	35							
7	Out	look	37							
8	Con	tributions	39							
	8.1	Paper I	39							
	8.2	Paper II	40							
	8.3	Paper III	40							
	8.4	Paper IV	41							
	8.5	Paper V	41							
	8.6	Paper VI	41							
	8.7	Paper VII	42							
Bi	Bibliography 43									

Chapter 1 Introduction

Robots are becoming ubiquitous and utilized in diverse application domains. Personal robots that can help with home or office chores are getting popular, and a trend to move away from preprogrammed robots operating in well-defined controlled environment has started. Programming robots for different tasks most often requires considerable cost and energy, and has to be done by experts. Therefore, finding proper solutions based on human's natural ways of learning for efficiently teaching robots new skills can reduce the complexity for end-users as well as saving resources. Humans usually acquire their skills through direct tutelage, observational conditioning, goal emulation, imitation and other social interactions (Scassellati, 1999b). This has opened a new area in human-robot interaction such that even non-roboticist users may teach robots to perform a task by simply showing how to accomplish it with a demonstration. The task can vary from a very simple action of "picking up a cup" to a complex one like "assisting a human agent to uncover victim from rubble in debris". The general technique is called Learning from Demonstration (LfD) or Imitation Learning (IL), and has been studied widely over the past decade. Both LfD and IL are used extensively in the robotics literature, but LfD is the adoption of insights from social sciences and neuroscience regarding the process of imitation in humans and animals. Therefore, both terms are often used interchangeably (also in the current thesis) due to their common prerequisites that root in the social sciences.

LfD provides a powerful way to speed up learning new skills, as well as blending robotics with psychology and neuroscience to answer cognitive and biological questions, brought to attention by for instance Schaal (1999) and, Demiris and Hayes (2002). Despite all its benefits, a number of challenges have to be tackled from different abstraction levels. These challenges and an overview of related work are discussed in chapter 2.

The tutor is a big part of LfD where the robot attempts to observe and learn not only the performed actions, but also tutor's intents. Correct intention recognition together with adequate action learning result in complete and flawless behavior reproduction, which allows the robot to affect the world in the same way as demonstrated. In theory and practice, there are different levels of complexity in imitating behaviors and they have been investigated in many studies (Meltzoff, 1988; Miklósi, 1999; Call & Carpenter, 2002). A few social learning mechanisms from biological systems have been introduced to extrapolate each kind of complexity. Sometimes these mechanisms are erroneously considered imitation while they more correctly should be categorized as pseudo-imitation. Such mechanisms are *response facilitation, stimulus enhancement, goal emulation* and *mimicking* (Fukano et al., 2006).

Response facilitation is a process by which an observer starts to exhibit a behavior from his existing repertoire by observing others performing the same behavior. Stimulus enhancement is a mechanism by which an observer starts to exhibit a behavior from his existing repertoire, due to exposure to an object with affordances that draw the observer's attention. Goal emulation is a process of witnessing others interacting with an object to achieve certain results without understanding how it is achieved, and then trying to produce the same results with the same object by its own action repertoire. Mimicking is a mechanism by which an observer starts to copy all actions performed by others without understanding their intentions.

True imitation is gained by reproducing observed actions of others using the same strategy to achieve the same goals. Thus, depending on what type of imitation is concerned, different requirements are needed.

In the current thesis, we propose methods of learning that mainly focus on understanding a tutor's intent, and identify what information is worth the robot's attention. We investigate human memory effects to discover mechanisms to influence and speed up the learning process in robots. The suggested methods are used to learn object affordances along with conditions to replicate the motor-actions that have the same effects to the world. Novel approaches are introduced to resolve ambiguities in demonstrations where insufficient information can mislead the robot to incorrectly infer the tutor's intent. The results of this work can also be used for shared control where the robot predicts actions according to the observed behavior. Depending on how successful the predictions are, the robot may then take over control and give the user more freedom to engage with other tasks. The tutor may also use a shared control system to teach the robot new behaviors when several demonstrations of a behavior are required.

1.1 Levels of Abstraction

LfD in robotics consists of different levels of abstraction, that each one refers to one aspect of learning. Mapping of sensory-motor information that produces an action to be performed by actuators is referred to low-level. In other words, a lowlevel representation of a learned skill is a set of sensory-motor mappings (Billard et al., 2008). These mapping can produce the same trajectories as observed during demonstrations or might be adapted to the robot's morphology but still result in the same actions. Many studies have addressed the problem of low-level learning and reproduction of behaviors. Among them, (Dillmann, 2004; Ekvall & Kragic, 2005; Calinon et al., 2007; Pastor et al., 2009; Billing & Hellström, 2010; Skoglund et al., 2010; Ijspeert et al., 2013) are especially worth mentioning. Another aspect of imitation is related to the demonstrator's intentions, goals and objects of attention, which here are considered high-level representations of skills, and sometimes referred to conceptualization or symbolic learning (Billard et al., 2008). Various techniques for learning the purpose of a demonstration, understanding tutor's intentions, and identifying what objects or elements in a demonstration are more important have also been developed, as described for instance in (Mahmoodian et al., 2013; Hajimirsadeghi et al., 2012; Cakmak et al., 2009; Erlhagen et al., 2006; Chao et al., 2011; Jansen & Belpaeme, 2006).

1.2 Objectives

This thesis heads for developing novel techniques for interactive learning particularly in LfD, in order to improve concept formation, intention recognition and ways to deal with ambiguities in demonstrations. The developed methods are part of an architecture that is particularly tailored for learning high-level aspects of demonstrations. The architecture employs techniques to sequentially learn and reproduce motor-skills in order to make the robot capable of affecting the world in the same way as demonstrated. The architecture uses four learning methods coupled with an attentional mechanism to identify the most important elements of the demonstration. These methods are also used to learn object affordances, thereby helping the robot to select appropriate sensory-motor actions in accordance with high-level perceptions. The architecture is then used for behavior arbitration and robot shared control.

1.3 Thesis Outline

The remaining chapters are organized as follows: Chapter 2 presents an overview of LfD; challenges and related work. Chapter 3 focuses on cognitive architectures and frameworks proposed in different studies, and to what extent they have influenced the current work. Chapter 4 is about learning methods and how an attention mechanism was developed. Chapter 5 introduces ambiguity and priming mechanisms. Chapter 6 describes fundamentals of shared control and its applications in LfD. Finally, some notes about future work along with summary of contributions are given in Chapter 7 and 8.

Chapter 2

Challenges in Learning from Demonstration

A successful robot learning from demonstration requires overcoming certain challenges, known as the "*Big Five*" (Dautenhahn & Nehaniv, 2002). Commonly not all the challenges are addressed in one single study and normally there are a few assumptions to mitigate the learning complexity. These challenges are introduced and related work is presented in the following sections.

2.1 Big Five

In order to overcome the challenges in LfD, "Big Five" central questions have to be answered: Who to imitate? When to imitate? How to imitate? What to imitate? How to evaluate a successful imitation? A thorough investigation of these research questions may enable construction of robots that are able to benefit from the utmost potential of LfD (Dautenhahn & Nehaniv, 2002). Among these questions "Who" and "When" are mostly left unexplored and the majority of approaches are proposed to tackle "What" and "How", which basically refer to learning and encoding skills respectively. In the current thesis we are addressing "What" and "When" while employing existing techniques from the "How" question.

2.1.1 Who to Imitate

Finding a proper solution for this question requires exhaustive studies in social sciences, since it is strongly connected to the social interactions between an imitator and a demonstrator. Choosing a demonstrator whose behavior can benefit the imitator is essential. Identifying which demonstrator's task is relevant and serves the imitator in some way requires evaluating the performance of the behaviors shown by the selected demonstrator (Alissandrakis et al., 2002).

2.1.2 When to Imitate

This aspect of imitation learning is also tied to social sciences, and is about identifying an appropriate time period to imitate. The imitator has to identify the beginning and end of a shown behavior, as well as deciding if the observed behavior fits in the current context (Alissandrakis et al., 2002).

2.1.3 What to Imitate

Depending on what aspects of a behavior are of interest, different approaches should be applied. In case of *actions*, the demonstrator's movements are relevant, so copying the exact trajectories is important. In other situations, the result and the *effects* of actions are considered important. This means that, the imitator may reproduce the observed behavior with a different set of actions, but the same goal is achieved (Zentall, 2001). According to Byrne and Russon (1998) there are two different modes of imitation that are distinct from each other: *action level* imitation is about matching minor details and style of sequential acts (i.e. pushing a lever) and *program level* imitation is about copying the structural organization of a complex process (i.e. picking, folding and chewing herbaceous plants shown by apes). The latter requires that the imitator is able to build hierarchical structures in order to learn coordinated sequence of actions to fulfill a goal.

When the robot attempts to imitate, it is crucial to understand which perceptual aspects of the behavior is relevant. Having the ability to detect saliency and focus on the relevant elements of a demonstrated behavior requires a sophisticated attentional mechanism (Breazeal & Scassellati, 2002b). Different attentional models have been proposed and evaluated. Some models use fixed criteria to selectively direct all computational resources to the elements of the behavior that have the most relevant information (Mataric, 2002), such as a specific color, motion speed or various depth cues (Breazeal & Scassellati, 1999).

In another model, which has been used in imitation learning, mechanisms for simultaneous attention to the same object or state in the environment use the concept of shared attention (Hoffman et al., 2006; Scassellati, 1999a).

2.1.4 How to Imitate

Once perception is completed and the robot has decided what to imitate, it has to engage an action within its repertoire to exactly replicate the same trajectories or achieve the same results. In case it does not know how to perform the observed action, the robot has to learn it by mapping perceptions into a sequence of motor actions related to its own body. Therefore, embodiment of the robot and its body constraints determine how an observed action can be imitated (Alissandrakis et al., 2002). Mismatch between the robot's and the demonstrator's morphology during the mapping process leads to the so called *correspondence problem* (Nehaniv & Dautenhahn, 2002). From a neuroscience perspective, the correspondence problem is explained by *mirror neurons* (Brass & Heyes, 2005; Iacoboni, 2009), which create shared context and understanding of affordances between imitator and demonstrator. Most robotics research is *a priori* that allows focusing on finding solutions for "How to imitate" by constraining design space and thereby fixating what, when and who to imitate (Dautenhahn & Nehaniv, 2002).

2.1.5 How to Evaluate Successful Imitation

Evaluation of reproduction of a demonstrated behavior determines if the robot was able to correctly answer the five questions described above. Sometimes, imitation is considered successful if the correct motor actions have been employed by the robot (Scassellati, 1999b). Most often, evaluation is based on the specific experimental setup and thus it is difficult to make comparisons of different results (Dautenhahn & Nehaniv, 2002). The evaluation may be done by the demonstrator or by an observer with vocal feedback, facial expressions or other kinds of social interaction.

In case of goal oriented imitation, successful imitation is interpreted as achieving the same results by executing appropriate actions from the observer's repertoire.

2.2 Other Challenges

Within the "Big Five" questions described above lie additional challenges for which a successful learning and reproduction system has to provide solutions. These challenges are for instance generalization, learning object affordances and sequence learning. These challenges may be considered as parts of big five and may or may not be addressed separately. In any case, resolving them enables development of more social and believable robots.

2.2.1 Generalization

An essential feature of any learning system is its ability to generalize. Generalization is a process of observing a set of training examples, identifying the significantly important features common to these examples and forming a concept definition based on these common features (Mitchell et al., 1986). Once a robot has learned to execute a task in a particular situation, it should be able to generalize and reproduce the task in different and unseen situations (Calinon & Billard, 2007). In the real world with a dynamic environment, it is crucial to be able to adapt and perform appropriate actions depending on the perceived situation. In contrast to early works in imitation learning that attempted to simply reproduce behaviors as copies of what had been observed, recent works often attempt to generalize across a set of demonstrations.

Generalization may be considered at the sensory-motor level (sometimes referred to as trajectory level), but also at the level of sequences of predefined motion primitives that accomplishes a task (Billard et al., 2008). In generalization at trajectory level, robot actuator movements are generalized such that the system creates generic representation of the motion for encoding different related movements. Generalization at the level of sequences of predefined motion primitives is about recognizing a task structure in terms of what actions are involved, and creating generic task structures to execute other related tasks. For a robot working close to humans in a dynamic environment with several objects and concepts, the capability to generalize one concept to another is essential. This high-level type of generalization is considered in this thesis. For instance, the robot may learn to clean the table when an empty cup is placed on it. The generalization ability helps the robot to perform the cleaning task also when an empty mug is observed on the table. In this way, object affordances are generalized such that even by perceiving objects of different type, the robot correctly performs the right task. The example shows that the problem not necessarily has well-defined solution, and the suitable level of generalization depends on the situation.

2.2.2 Sequence Learning

Most complex tasks performed by humans comprise sequences of actions executed in the proper order. Therefore, sequence learning plays an important role in human skill acquisition and high-level reasoning (Sun & Giles, 2001). When humans learn sequences, the learned information consists of both sequences of stimuli and corresponding sequences of responses (Clegg et al., 1998). Thus, humans react to a stimulus based on the associated learned response. The same principles are considered while developing sequence learning in robots. In robotics, low-level sequence learning of sensory-motor states is done by utilizing, for instance, Hidden Markov Models (HMM) (Vakanski et al., 2012), Artificial Neural Networks (ANN) (Billard & Hayes, 1999) or Fuzzy Logic (Billing et al., 2012). High-level aspects, such as task goals, are learned by, for instance, conceptual spaces, which are knowledge representation models for intentions behind demonstrations (Cubek & Ertel, 2012). The Chain Model, a biologically inspired spiking neuron model that aims at reproducing the functionalities of the human mirror neuron system, was proposed by Chersi to encode the final goal of action sequences (Chersi, 2012). In another study, based on reinforcement learning and implicit imitation, sequences of demonstrator's states (e.g. demonstrator's location and limb positions) was used to learn how to combine set of action hierarchies to achieve sub-goals and eventually reach the desired goal (Friesen & Rao, 2010). Lee and Demiris (2011) used stochastic context-free grammars (SCFGs) to represent high-level actions and model human behaviors. First they trained the system with a set of multipurpose low-level actions with HMMs, and then they defined high-level task-independent actions (goals) that comprised previously learned low-level actions as vocabulary. A human-behavior model, with low-level actions associated to symbols, was then created by utilizing SCFG.

In the current thesis, we propose an architecture for goal-based sequence learning and reproduction of high-level representations of behaviors. In our novel approach, semantic relations between observed concepts/objects and executed actions are learned and generalized in order to achieve demonstrated goals (Fonooni et al., 2013). In Chapter 3, the proposed architecture and related work are presented.

2.2.3 Learning Object Affordances

The quality of an object defines its potential for motor actions to be performed on it and obtained upon execution of an action towards the object (Gibson, 1979). Affordances are defined as relations between actions, objects and effects that are used to predict the outcome of an action, plan to reach a goal or to recognize an object and an action. A noteworthy feature of affordances is their dependence on the world and on the robot's sensory-motor capabilities. Moreover, affordances require a set of primary actions as prior information. In robot imitation learning, affordances have been used for action recognition while interacting with the demonstrator (Montesano et al., 2008). Lopes et al. (2007) proposed a framework for robot imitation based on an affordances model using Bayesian networks to identify the relation between actions, object features and the effects of those actions. Dogar et al. (2007) developed a goal-directed affordance based framework to allow the robot to observe effects of its primitive behavior on the environment, and create associations between effects, primitive behaviors and environmental situations. The learned associations helped the robot to perform more complex behaviors in the reproduction phase. In work by Thomaz and Cakmak (2009), Socially Guided Machine Learning (SGML) was used to investigate the role of the teacher in physical interaction with the robot and the environment in order to learn about objects and what actions or effects they afford. Lee et al. (2009) showed the efficiency of using object affordances in measuring the relevance of objects for a task, and thus helping the robot to engage appropriate low-level action.

In the current thesis we introduce techniques to learn object affordances and employ them to arbitrate a behavior. These techniques are discussed in Chapter 4.

Chapter 3

Cognitive Architecture for Learning from Demonstration

In many robotics applications, especially those involving imitation learning, structures are defined and guidelines for information flow are specified in an architecture. Depending on objectives, hardware design, behavioral repertoire and perceptual inputs, different architectures have been proposed (Breazeal & Scassellati, 2002a; Chella et al., 2006; Gienger et al., 2010; Bandera et al., 2012; Demiris & Khadhouri, 2006). Apart from basic principles of all cognitive architectures, there are common key components in most architectures for robot imitation learning. According to Langley et al. (2009), principles are aspects of an agent, which are essential for all mechanisms to work in different application domains: i) short and long-term memories ii) representation of elements residing in these memories iii) functional processes operating on these structures. In addition, according to Vernon et al. (2007), a cognitive system that entails an architecture for imitation learning, constitutes loosely coupled components that cooperate to achieve a cognitive goal. It must be able to adapt, self-alter and anticipate actions and events that appear over a period of time.

Architectures for robot imitation learning contain common key components for cognitive and motor capabilities of the robots. These components are perception, knowledge management, learning and motor command generation. In the following section the above mentioned architectures are discussed briefly.

3.1 Related Work

In the study by Breazeal and Scassellati (2002a), several research problems regarding robot imitation learning are outlined. Their generic control architecture was developed for the Cog and Kismet robots. The architecture discriminates between low- and high-level perceptions based on how much processing is required for the information delivered by each sensor. Learning functionality is not explicitly handled in one specific component but exist in each one of the components. The *Attention System* is responsible for regulating attention preferences according to motivational states while learning new motor skills. The *Behavior System* is designed to infer goals and select appropriate behaviors based on perceptions and motivational states. The result of the behavior selection is transferred to the *Motor System* for execution on the robot. Figure 3.1 depicts the architecture and involved components.



Figure 3.1: Architecture proposed by Breazeal and Scassellati (2002a) intended to be used on Cog and Kismet (figure adapted by author).

Chella et al. (2006) proposed an architecture that coupled visual perception with knowledge representation for the purpose of imitation learning. *Conceptual space theory* (Gärdenfors, 2000) is used in their architecture to learn movement primitives from demonstrations and then represent them in generated complex tasks. The architecture functionality has been evaluated on a robotic arm equipped with a camera. Figure 3.2 illustrates the architecture and its components. The architecture consists of three main components. The *Subconceptual Area* is responsible for perception of data from vision sensors, and processing to extract features and controlling robotic system. The *Conceptual Area* is responsible for organizing information provided by the *Subconceptual Area* into categories by using conceptual spaces. Finally, high-level symbolic language has been used to represent sensor data in the *Linguistic Area*. The architecture was designed to work in both observation and imitation modes.



Figure 3.2: Architecture proposed by Chella et al. (2006) (figure adapted by author).

Gienger et al. (2010) proposed a three-layered architecture based on prior works in the field of imitation learning focusing on movement control and optimization. The aim was to provide solutions for the generalization problem and accomplishing a task in different situations. Figure 3.3 depicts modules that are included within the architecture. The *Reactive* layer is responsible for handling perceptions in the system. The *Persistent Object Memory (POM)* was used as an interface between the system and the real world, and includes a model of the world as well as of the robot. While the teacher demonstrates a behavior, the *Movement Primitives* layer normalizes observed movements using a *Gaussian Mixture Model (GMM)* and represents them by mean value and variance. Finally, in the Sequence layer, which acts as a procedural memory, sequences of movement primitives are maintained. In the described experiments, predefined primitives for different tasks such as grasping were used, and all learned movements were embedded within predefined locations in the sequence.



Figure 3.3: Architecture proposed by Gienger et al. (2010) (figure reused by permission).

In another study by Demiris and Khadhouri (2006), a hierarchical architecture named HAMMER based on attentive multiple models for action recognition and execution was introduced. As illustrated in Figure 3.4, HAMMER utilizes several inverse and forward models that operate in parallel. Once the robot observes execution of an action, all action states are delivered to the system's available inverse models. Thus, corresponding motor commands representing the hypotheses of which action was demonstrated will be generated and delivered to the related forward model so it can predict the teacher's next movement.

3.1 Related Work



Figure 3.4: The basic architecture proposed by Demiris and Khadhouri (2006) (figure adapted by author).

Since there might be several possible hypotheses, the attention system is designed to direct the robot's attention to the elements of the action to confirm one of the hypotheses. Figure 3.5 depicts the complete design of the architecture including forward and inverse models together with the attention system for saliency detection. The architecture was tested and evaluated on an ActiveMedia Peoplebot with camera as the only sensor.



Figure 3.5: The complete architecture proposed by Demiris and Khadhouri (2006) (figure adapted by author).

In addition to aforementioned studies, other works regarding general cognitive architectures such as ACT-R (Anderson et al., 2004) and SOAR (Laird, 2008), model for reading intentions (Jansen & Belpaeme, 2006) and goal-directed imitation learning frameworks (Tan, 2012) have been reviewed. Furthermore, works by Kopp and Greaser (2006) and, Buchsbaum and Blumberg (2005) also inspired the design of our architecture.

3.2 Proposed Architecture

The rationale behind developing a new architecture while several well-proven ones already exist is a set of new requirements and a new approach to emulating goals in the framework of imitation learning. In the design of our architecture, we have considered the hardware setup, robots capabilities and the domain in which the robots are intended to be used.

Our approach to goal emulation and learning high-level representation of behaviors is to employ a semantic network. In this thesis, prior knowledge of the domain is provided as an ontology represented by a core semantic network that acts as the robot's long-term memory and contains all necessary concepts and objects that the robot is able to work with. In our case, high-level concepts such as objects (e.g. B1, Sph1), object categories (e.g. Basket, Spherical), features (e.g. Shape, Size, Color), and feature values are represented by nodes, while their associations are represented by directed links. Furthermore, the strength of associations is represented by numerical weight values for each link, and each node has three numerical attributes including activation, energy and priming values. The semantic network is used to build semantic relations between robot perceptions and learned behaviors, we denote this coupling *context*, and also refer to it as sub-behavior. A context includes presence of objects, concepts and environmental states. During high-level learning, contexts are formed by observing a tutor's demonstration. A complex behavior, also denoted *goal*, consists of several sub-behaviors that are executed in sequence. Not only context formation is taken into consideration during learning but also sequencing. Sequencing is semi-automatic, and comprises one part related to how the tutor conducts the demonstration, and one part related to the system that associates the subsequent context to the preceding one. At the current stage of our architecture development, by finalizing learning of one context and starting learning of another, the system connects both contexts together according to their order in the demonstration.

Once high-level learning is completed, low-level actions will be associated to each one of the learned contexts. Depending on which low-level controller mechanism has been used, the contexts and low-level actions are associated differently. This task is elaborated in section 3.2.3.2. Low-level actions can be learned simultaneously to the contexts, or they can be hard-coded primitives existing in the robot's repertoire. When the complex behavior is reproduced, the actions of each context are executed in the right sequence, initiated by a context selection process.

We have proposed several variations of our architecture, first with low-level learning and control for behavior arbitration (Fonooni et al., 2012) and also with action-primitives and a goal management system to understand the tutor's intentions, as well as behavior arbitration (Fonooni et al., 2013). Figure 3.6 illustrates the complete architecture and is followed by a description of the individual components.



Figure 3.6: The developed architecture for low- and high-level behavior learning and reproduction.

3.2.1 Hardware Setup

In our experiments, we used the Robosoft Kompai robot, which is based on the RobuLAB10 platform and robuBOX software (Sallé et al., 2007), as well as Husky A200 Mobile Platform operated by ROS (Quigley et al., 2009) and Lynxmotion AL5D robotic arm. Additional information about our robotic platforms and exhaustive scenario descriptions are well presented in (Jevtić et al., 2012) and (Kozlov et al., 2013). In order to facilitate the process of object recognition, RFID sensing

on the Kompai, and ARToolKit marker recognition tools on the Invenscience arm mounted on the Husky A200 platform were utilized. A database of known objects was linked to the RFID and marker sensors to retrieve properties of the perceived objects. Finally, for mapping and navigation, a laser scanner was used.

3.2.2 Perception Unit

All used sensors are included in the perception unit. Sensors are categorized into high- and low-level according to the type of information they provide and which controller is the main consumer. Laser data is considered low-level while RFID and marker recognition, included in visual input, are considered high-level. Useful information is extracted from all available input channels by high- or low-level controller's request and delivered to the caller in the required format.

3.2.3 Cognition Unit

As mentioned earlier, the most common components of all cognitive architectures for imitation learning are knowledge management, learning and control which are also considered in our architecture. The cognition unit is designed such that it can act as the robot's memory for storing both learned and preprogrammed information. It also provides learning facilities with attention mechanisms for recognizing the most relevant cues from perceptions. Making decisions on what actions to perform such that the behavior complies with a specific goal, and providing required structure for behavior arbitration are other responsibilities of the cognition unit.

3.2.3.1 High-Level Controller

This module has strong impact on both learning and reproduction of behaviors. Learning a new context, which is an association between the behavior to be learned and perceptions the system regard as relevant, requires an attentional mechanism to identify the most important cues in the demonstrated behavior. A semantic network functions as a long-term memory of the robot. The mechanisms for storing and retrieving information from semantic networks are discussed in Chapter 4. Each context is part of the semantic network and is represented by a node and semantic relations to all related perceptions represented by links. The learning module is connected to the perception unit and also to the semantic network.

Reproduction of a behavior starts by a behavior arbitration mechanism, which is one of the key parts of the proposed architecture. By definition, behavior arbitration is a process of taking control from one component of an architecture and delegate it to another (Scheutz, 2002). The robot should reproduce learned behaviors when relevant cues such as environmental states, perceived objects or concepts are present. These cues affect the activation of learned contexts, which control the arbitration process. This is done by recognizing all possible contexts that conform to the assigned goal, and selecting the most relevant one to be handed over to lowlevel controller for action execution. Context learning and the selection processes are thoroughly explained in Chapter 4.

3.2.3.2 Low-Level Controller

This module is responsible for learning and selecting motor actions that are associated to the contexts. In case of learning a new action in parallel to learning context, *Predictive Sequence Learning (PSL)* is used. This technique is designed to build a model of a demonstrated sub-behavior from sequences of sensor and motor data during teleoperation, and results in building a hypotheses library. The learned sequences are used to predict which action to expect in the next time step, based on the sequence of passed sensor and motor events during the reproduction phase (Billing et al., 2010). Learning is finalized by associating the learned context with a set of hypothesis in the hypotheses library.

In another alternative approach, a set of preprogrammed Action-Primitives are used. A *primitive* is the simplest movement of an actuator in the robot's repertoire that requires a set of parameters for execution. As an example, grasping is a primitive with a set of parameters identifying where and how strong to do gripping actions with the robot's wrist actuator. Depending on the robot's capabilities, different primitives are defined and developed. In this work primitives are implemented using behavior-based visual servoing as described in (Fonooni & Hellström, c) and inverse kinematic models in (Kozlov et al., 2013). The image-based visual servoing (IBVS) is a type of closed-loop control mechanism that uses visual feedback to control the robot. The 2D image is used to track and position a manipulator by reducing the image distance error between a set of current and desired image features in the image plane (Kragic et al., 2002). Behavior-based visual servoing is similar to IBVS in many respects but uses principles of behavior-based robotics where a number of independent behaviors running in parallel are defined (Mataric, 1997). Each behavior uses specific features of an image to control the manipulator, and form together with the other behaviors a desired primitive. In another implementation of primitives, motor babbling is used to collect sensory-motor data from the robot manipulators. Motor babbling is inspired by body babbling of infants (Meltzoff & Moore, 1997) and defined as a process of performing a repetitive random motor command to move joints in order to obtain a mapping between joint movements and their end states (Demiris & Dearden, 2005). The collected data from the Invenscience arm's joint angles and positions are used to train an artificial neural network to learn the mapping from the target object position to the arm commands. With this method, the inverse kinematic model of the arm is learned through self-explorations.

The Action module is an interface between contexts and primitives that retrieves information about the object of attention from the context and passes it as parameters to the primitive in a required format. The rationale behind defining actions is the different abstraction levels of contexts and primitives. There are no intersections between the two but they need to be integrated in order to successfully perform a behavior. The main responsibility of the low-level controller during the learning period and while using action-primitives, is to identify which primitive has been executed while teleoperating. Thereby, the system is able to automatically associate a learned context and an executed primitive through its action. Every primitive that is associated to an action, is preprogrammed. Therefore, context is only associated to an action.

In the reproduction phase, once an identified context is delivered from the high-level controller, its corresponding action or hypothesis (depending on whether Action-Primitives or PSL are engaged) is identified and passed to the output unit for execution in the robot's actuators.

3.2.3.3 Goal Management

This component serves two purposes: i) handling sequences in learning and reproduction of behaviors ii) motivating the robot to reproduce previously learned behaviors by understanding the tutor's intention. As mentioned earlier, throughout the learning process, a complex behavior is decomposed into sub-behaviors, which are demonstrated individually and stored as separate contexts in the semantic network. The learned contexts are organized in a sequence when learning of a sub-behavior ends.

In the reproduction phase, a user may explicitly specify a goal for the robot through a user interface. The robot explores the environment in search of stimuli that activate contexts and then executes their corresponding actions. The contexts must be activated in the same order as they were learned. Therefore, the robot constantly explores the environment until the required stimulus for activating the right context is perceived. Another form of behavior reproduction is to use the motivation system to implicitly specify a goal for the robot. The motivation system contains priming, which is a mechanism that biases the robot to exhibit a certain behavior when stimulating the robot with a cue. In Neely (1991), priming is defined as an implicit memory effect that speeds up the response to stimuli because of exposure to a certain event or experience. Anelli et al. (2012) showed that within the scope of object affordances, priming increases the probability of exhibiting a behavior by observing a related object or concept. Once the robot is primed, contexts related to the priming stimuli are activated and, through a bottom-up search from the contexts, the most plausible goal will be identified and selected. Thereby, the actions of the relevant contexts in the selected goal will be performed in sequence. Further explanation of the priming mechanism is given in Chapter 5.

3.2.4 Output Unit

All actions performed by the robot are executed through the output unit, which retrieves a selected primitive and its set of parameters to generate appropriate motor commands. In the proposed architecture, two ways of teaching the robot new motor-actions are developed: i) direct teleoperation via joystick, which requires the tutor to completely engage with the demonstration of an action and ii) shared control, which demands less intervention and can mitigate the workload of the tutor. The latter technique is described in Chapter 6.

Chapter 4

Learning High-Level Representation of Behaviors

This chapter presents our developed learning methods along with attentional mechanisms to learn high-level representations of behaviors. The high-level representation of a behavior refers to the aspects of the behavior that consist of goals, tutor's intentions and objects of attention. Hence, learning high-level representations of behaviors relates to understanding the tutor's intentions and what elements of the behavior that require attention.

As mentioned earlier, most works on high-level learning deal with conceptualization and symbolization. Our approach to conceptualize observed behaviors is to employ semantic networks. Nodes and their semantic relations represent the robot's perception and understanding of high-level aspects of behaviors. The learning process aims at forming semantic relations of noteworthy concepts, manipulated objects and environmental states throughout the demonstration. The result is denoted context. The role of a context is twofold: i) it retains important elements of the learned behavior and thus answers the question of "what to imitate" ii) it contains necessary conditions to exhibit a behavior and thus answers the question of "when to imitate". The latter is utilized when the robot perceives the same, or similar, objects or concepts as during learning. This leads to context activation and execution of corresponding actions in the robot.

4.1 Why Semantic Networks

Depending on the field of study, semantics is defined in various ways. In linguistics, it refers to the meaning of words and sentences. In cognitive science, it often refers to knowledge of any kind, including linguistic, non-linguistic, objects, events and general facts (Tulving, 1972). Many cognitive abilities like object recognition and categorization, inference and reasoning along with language comprehension are powered by semantic abilities working in semantic memory. Therefore, questions like "How to understand the purpose of an action?" or "How to understand which

items or events must treated the same?" cannot be answered adequately without investigating the semantics abilities (Rogers, 2008).

Semantic networks is a powerful tool to visualize and infer semantic knowledge that is expressed by concepts, their properties, and hierarchies of sub and superclass relationships. Semantic networks have been widely used in many intelligent and robotics systems. In early days, hierarchical models of semantic memory were developed, based on the fact that semantic memory contains a variety of simple propositions. An inference engine based on syllogisms was used to deduce new propositional knowledge. Empirical assessment of the proposed model showed that verifying a proposition that is much more common takes more time depending on the number of nodes traversed in the hierarchy (Collins & Quillian, 1969). The typicality was not modeled efficiently in early implementations. For instance, a system could not infer that a chicken is an animal, as fast as it infers that a chicken is a bird. This is due to the hierarchies in the defining semantic relations. However, according to Rips et al. (1973), humans are inferring "chicken is an animal" faster due to the typicality that influences the judgment. By revising the early implementations, Collins and Loftus (1975) introduced a new spreading activation framework that allows direct links from any node to any concept, but with different strengths. This was particularly efficient since it speeded up retrieval of typical information due to their stronger connection, compared to less typical concepts.

Spreading activation is a process based on a theory of human memory operations that allows propagation of activation from a source node to all its connections according to their strength (Crestani, 1997). In the spreading phase, the amount of activation to be propagated is calculated, and all connecting nodes receive activation according to their strength, which is represented by weights.

4.2 Learning Methods

Learning a high-level representation of a behavior requires prerequisites including prior knowledge about the domain where the robot is intended to operate. In our case, this knowledge is maintained in a core semantic network and encompasses many aspects of the domain, such as available objects to manipulate, their respective properties, concepts, environmental states and learned sub-behaviors (contexts). The contexts also become part of the core semantic network after learning is completed. Since a semantic network is used as a model of the world, all items are represented as nodes that have certain properties such as activation values and energy levels that are used for the spreading activation process. Links define semantic relations and contain weight values that are also used in the spreading process. Some nodes represent perceivable objects in the environment and are connected to RFID or marker sensors. After each readout, these nodes receive activation and propagate it according to the applied settings. Through the spreading activation mechanism, this results in activation of several nodes, including object features and categories.

The learning process begins with decomposition of the behavior by the tutor

into sub-behaviors. Teleoperation and shared control are used to demonstrate a sub-behavior to the robot that observes the environment with the sensors. During observation, a learning network is created that contains a new context node connected to all perceived objects and features. Due to the spreading activation process, even non-perceived objects may receive activation and are connected to the context node. All sensors are read within a certain frequency and at each time step, the learning network is updated and activation values of all affected nodes are stored in arrays. In case of demonstrating the same sub-behavior multiple times, the learning network and activation arrays for each demonstration are saved separately for further processing. Once all the demonstrations are finished, the system decides which elements of the demonstrations are most relevant. Since the robot is able to perceive many things that may not be relevant for the goals of the sub-behavior or the tutor's intention, there is a need for an attentional mechanism to extract important information from the demonstrations. Thereby, we introduce several methods for identifying and removing irrelevant nodes from the final learning network. Based on which method is selected, weight values for the remaining nodes are calculated. Finally, the core semantic network is updated according to the remaining connections and their associated weight values from the learning network. Figure 4.1 depicts all steps in the learning process regardless of which method is used.



Figure 4.1: Steps of the learning process.

In this thesis, four different context learning methods including mechanisms for directing the robot's attention to the relevant elements of demonstrations are introduced.

4.2.1 Hebbian Learning

This method is inspired by the well-known Hebbian learning algorithm for artificial neural networks. Its basic tenet is that neurons that fire together, wire together (Hebb, 2002). Hebb suggested that the weight value for the connection between two neurons is proportional to how often they are activated at the same time. In our case, neurons are replaced by nodes in the semantic network, and all robot perceptions are mapped to their corresponding nodes and connected to the context node. This method does not contain any attentional mechanism to identify relevant

information but rather keeps all the nodes and strengthen connection between those that are activated together more often.

4.2.2 Novelty Detection

This method is inspired by techniques for detecting novel events in the signal classification domain. While there are many novelty detection models available, in practice there is no single best model since it depends heavily on the type of data and statistical features that are handled (Markou & Singh, 2003). Statistical approaches to novelty detection use statistical features to conclude whether data comes from the same distribution or not.

Our approach begins with environment exploration guided by teleoperation to create a history network. In this phase, no demonstrations of desired behaviors are conducted by the tutor, and the history network only contains environmental states. In the next phase, the tutor performs the demonstration and the system builds a learning network accordingly. After collecting required data, a t-test is run to check which nodes have activation values with similar distribution in both history and learning networks. Nodes with different distribution are considered relevant, and thus remain connected to the context node. The weight value of each connection is calculated based on the node's average activation value, and how often the node received activation during both history and learning phases.

With this approach, the attentional mechanism looks for significant changes between the history and learning phases. Nodes that were less, or not at all, activated during the history phase are considered important and most relevant.

In our first paper (Fonooni et al., 2012), we elaborate this technique in detail and evaluate it using a Kompai platform. The test scenario is to teach the robot to push a moveable object to a designated area labeled as storage room.

4.2.3 Multiple Demonstrations

An alternative technique, to some extent the opposite of Novelty Detection is Multiple Demonstrations. The main differences are the number of demonstrations and the way attentional mechanism works. The history phase is removed, and the tutor repeats the demonstration at least two times. During each demonstration, a learning network and activation arrays of nodes are formed and stored. Afterwards, a one-way ANOVA test (Howell, 2011) is run on the datasets of activation values to determine for which nodes the distributions do not vary between demonstrations. The attentional mechanism in this method searches for insignificant changes in all demonstrations. Therefore, nodes with least variation in their activations between all demonstrations are considered relevant. Weight values are calculated according to the nodes' average activation values and their presence in all demonstrations.

Paper II (Fonooni et al., 2013) describes the Multiple Demonstrations technique in an Urban Search And Rescue (USAR) scenario with a Husky A200 platform.

4.2.4 Multiple Demonstrations With Ant Algorithms

In a variation of the Multiple Demonstrations technique, Ant Systems (Dorigo et al., 2006) and Ant Colony Systems (Dorigo & Gambardella, 1997) are used as a substitution for the one-way ANOVA test. This technique is shown to be more intuitive and efficient in situations where ANOVA cannot be used to successfully determine the relevant nodes due to statistical constraints. The learning method is built on computational swarm intelligence, which results in emergent patterns and pheromone maps. The purpose of applying ant algorithms is to find and strengthen paths that can propagate higher activation values to the context node. Having fewer intermediate connections between the source node that receives activation and the context node, increases the amount of propagated activation. Therefore, the nodes closest to the context node are considered more relevant, and thus weight values of remaining connections are calculated based on the amount of laid pheromones.

Paper III (Fonooni et al., a) describes a combination of the Multiple Demonstrations method and ant algorithms, and presents results from experiments on learning object shape classification using a Kompai robot. Paper V (Fonooni et al., b) presents an attempt to identify a tutor's intents by blending an Ant System algorithm with a priming mechanism.

4.2.5 Comparison of Methods

Due to the differences between the introduced learning methods, there is no single best method for learning all kinds of behaviors. Therefore, methods have been evaluated according to the type of data they are able to process and scenarios in which they can be more efficient. Table 4.1 lists our learning methods with their respective features and in what conditions they can serve best.

As Table 4.1 shows, the Hebbian learning approach is used when all perceptions are relevant to the learned sub-behavior. Thus, every perception is considered important and must remain connected.

Novelty Detection is mostly successful in situations where the robot is equipped with several sensors and may perceive a large amount of information that is not directly relevant to the behavior. As an example, an ambient light or environment temperature can be sensed if the robot has proper sensors, but this information may not be relevant to the goals of the demonstration or tutor's intention. The Novelty Detection technique determines what is unchanged during the history and learning phases, and regards these features as unimportant.

Multiple Demonstrations is the best solution if the demonstrations are conducted almost in the same way, and the environment is free from noise. However, if the demonstrations differ significantly, the risk of not recognizing relevant nodes increases dramatically.

Multiple Demonstrations with ant algorithms is more noise tolerant, but still requires that the demonstrations are very similar.

An important limitation with all introduced methods is that none of them are able to learn a behavior that requires understanding of absence of objects. In addition, quantitative values cannot be handled in a simple way. For instance, learning to clean a table when no human is seated, or to approach a group of people with exactly three persons, needs special considerations with the presented learning methods.

Method	Number of Demonstra-	Core al- gorithm	Attentional mechanism	Condition
	tions			
Hebbian	One	Hebbian	None - Nodes	When every
Learning		Learning	that fire	observation is
			together,	relevant to
			wire together	the behavior
Novelty	One	T-Test	Looks for	When the
Detection			significant	robot
			changes in	perceives
			the history	numerous en-
			and learning	vironmental
			phases	states that
				are not
				relevant to
				the behavior
Multiple	At least two	One-way	Looks for	Not noisy
Demonstra-		ANOVA	insignificant	environment
tions		Test	changes in all	with only
			demonstra-	slight
			tions	differences
				between
				demonstra-
				tions
Multiple	At least two	Ant	Looks for the	Noisy
Demonstra-		System	nodes that	environment
tions with		(AS) and	can	where the
ACO		Ant	propagate	robot can be
algorithms		Colony	higher	easily
		System	activation to	distracted
		(ACS)	the context	
			node	

Table 4.1: Comparison of the developed learning methods

4.3 Generalization

One of the main challenges in imitation learning is the ability to generalize from observed examples and extend it to novel and unseen situations. Generalization in this work refers to extending associations of objects and concepts that already connected to the context node to less-specific ones. Figure 4.2 shows an example of generalization in terms of extending concepts for learning to find a human.



Figure 4.2: An example of concept generalization.

The robot should learn to look for a human and is shown a demonstration where the robot moves toward John. This will associate the John node to the Find Human context node. The system correctly associates perceptions to the context, but what the robot learned cannot be used in any other situation. Therefore, generalization of the John concept is needed if the intention is to teach the robot to repeat the behavior when any human is observed. This is achieved by spreading activation from the John node to the less-specific Human node. As a result, the Human node, along with other specific humans, is also considered part of the context and as a result, observing any humans will trigger the Find Human context. The degree of generalization is controlled by each node's energy value and the decay factor that is distance constraint to control how much energy or activation is depleted when spreading to neighboring nodes. The generalization of concepts is further demonstrated in Paper III (Fonooni et al., a).

Chapter 5

Ambiguity in Demonstrations

Assuming that the tutor's demonstrations are always complete and flawless, contradicts reality in particular when a naive tutor teaches the robot new behaviors. There are major factors that prevent the robot from perfect learning. One of the main reasons why a demonstration sometimes is not sufficient to infer the tutor's intention, is ambiguity in the demonstration. In real-world learning scenarios with numerous objects and features to perceive, identifying the most relevant ones is essential for understanding the tutor's intents. Normally, there is no priority between perceptions, which introduces ambiguity in the following sense. In a learning session where objects with different shapes and colors are shown to the robot and only one is collected by the tutor without providing additional information, there is a high possibility of incorrectly identifying the tutor's intent, which may be to collect objects with a specific color and/or shape. Even with repetition of the same behavior, this ambiguity may remain. In our recent work (Fonooni et al., b) we attempt to provide a novel solution to learn from such ambiguous demonstrations where repeating or better sensing cannot make the tutor's intent clear. Our approach is inspired by human memory model and takes advantage of a priming mechanism to bias the robot prior to learning and thereby reducing ambiguity.

5.1 Ambiguity

In various studies, ambiguity has been addressed differently in the context of LfD (Breazeal et al., 2006; Chernova & Veloso, 2008; Bensch & Hellström, 2010; Carlos Fernando Morales & Fernando De la Rosa, 2013; Cederborg & Oudeyer, 2014). Ambiguity often relates to insufficient sensing or perception, such as in the example above where one demonstration maps to several possible behaviors. Differences in robot and teacher perspectives during demonstrations may lead to another kind of ambiguity due to visual occlusion (Breazeal et al., 2006; Breazeal, 2009). A suggested method is to allow the robot to view the task from the tutor's perspective

and simulate his/her beliefs in order to identify intentions. Psychological studies of humans while attempting to assimilate beliefs of others show that putting oneself in other people's point of view results in better understanding of their beliefs (Flavell et al., 1992; Tversky et al., 1999). The same technique has been used to design a reasoning skill for reducing ambiguity proposed by Warnier et al. (2012).

In the work by Taylor et al. (2011), the authors conducted a set of experiments with unsuccessful and ambiguous demonstrations, which caused the learned policy to perform poorly during the reproduction phase. Their approach was to combine LfD with reinforcement learning and to use collected data from demonstrations to learn generalized rules and apply them to bias the reinforcement learning. Argall et al. (2009) defined ambiguity as inconsistencies between multiple demonstrations. A possible solution is to provide more demonstrations to reduce the ambiguous elements. In the study by Cakmak and Thomaz (2012), a natural language dialog between the robot and the tutor allows asking questions to unify interpretations of demonstrations from both robot and tutor perspectives. Cederborg and Oudeyer (2013) investigate several forms of ambiguity and tackle them by integrating techniques from computational models of language acquisition and models of motor skill learning from demonstration.

Our notion of ambiguity is inspired by (Bensch & Hellström, 2010) where multiple interpretations of a single demonstration are possible. The latter notion takes into account the high-level aspects of demonstrations and investigates solutions to eliminate irrelevant interpretation of tutor's intent by utilizing a priming mechanism.

5.2 Priming

Previous exposure to a stimulus often has significant impact on behavior selection and performance when subjects engage in tasks related to the observed stimulus (Neely, 1991). This effect is known as priming and is an implicit memory effect that unconsciously changes and speeds up the response to stimuli through exposure to a certain event or experience (Ochsner et al., 1994). Many works have studied the effect of exposure to visual or auditory signals prior to learning and recognition tasks with the purpose of understanding human memory effects (Neely, 1977; Tulving & Schacter, 1990; Maxfield, 1997; McNamara, 2004; Huber, 2008). Once a subject is primed, associations related to the shown stimuli are activated in the subject's memory by a spreading activation mechanism. Thus, objects and concepts that are associated together due to repetitive observations at the same time, are fetched faster from the memory. This is also known as positive priming which indirectly speeds up memory processes. In contrary, negative priming is used to slow down the processes and train the memory to ignore specific stimuli (Tipper, 1985). In another categorization, priming is divided into conceptual priming that relies on the semantic meanings of stimuli (Vaidya et al., 1999) and perceptual priming that affects perception and identification of related or the identical stimuli (Wiggs & Martin, 1998). The priming effect normally remains for a short period of time unless it is reinforced by repetition (Brown, 1996).

Further studies of priming in neuroscience show that some neural effects are caused by repeated experience (Henson & Rugg, 2003; Maccotta & Buckner, 2004; Wig, 2012) and particular neural mechanisms such as repetition suppression underlie priming. Repetition suppression explains how repeatedly presenting an object strengthens connections between neurons that form essential features of the object (Wiggs & Martin, 1998).

Priming is done in two stages and starts with a study stage in which a subject is exposed to a stimulus. The stimulus can be objects, words, pictures or features of an object. The second stage is the testing, which happens after a pause by presenting the same or reduced cues of the previously shown stimulus (Tulving & Schacter, 1990).

5.3 Priming to Resolve Ambiguity

Ambiguity caused by several possible interpretations of a demonstration is a serious problem in LfD since the tutor rarely wants the robot to repeat all perceived aspects of a demonstration. Although the problem often can be resolved by providing more demonstrations, this approach leads to slow learning. Thus, resolving ambiguity and speeding up learning by a single approach is very appealing. In the current thesis, priming is the pre-activation of nodes stored in the core SN, and is used to bias and speed up the learning process (Fonooni et al., b). The robot may be primed with objects, features, or concepts that directly or indirectly relate to the tutor's intents. In this way, the attention is directed towards elements that are relevant for the learning. This makes it possible to recognize the tutor's intentions in a less ambiguous way. Priming may also affect the reproduction phase by biasing the robot to arbitrate between behaviors as suggested in (Fonooni et al., 2013).

Ambiguity in Demonstrations

Chapter 6 Shared Control

In many robotic application domains, the need for teleoperated robots that can help to accomplish complex and tedious tasks has rapidly increased. Depending on the intricacy of the task, different levels of automation may be applicable. The degree of automation can be categorized into direct teleoperation, shared control and fully autonomous (Sheridan, 1995). The direct teleoperation does not require the robot to recognize user's intentions while it can easily become exhausting and unsuitable for complex tasks. Contrary to direct teleoperation, fully autonomous operation requires no interference from the user and the robot is capable of carrying out the task without user cooperation. However, fully autonomous operation is currently restricted to highly structured domains and static environments (Bekey, 2005). Moreover, sophisticated high-level robot intelligence capable of managing complex tasks is required. The objective of shared control teleoperation is to exploit synergy from both human and robot such that a user can complete a control task with less effort by accrediting the robot to carry out parts of the task, and intervening only when the robot is not performing according to the user's intention. The degree of shared control is typically specified based on the required amount of user intervention, and for how long the robot can be neglected (Goodrich et al., 2003).

Numerous control architectures have been introduced to provide different levels of autonomy for robot-operator cooperation (Hasemann, 1995; Fong et al., 2001; Dalgalarrondo et al., 2004; Armbrust et al., 2010). Most of the notable architectures have common prerequisites to be implemented. These requirements are comprised of mechanisms to assist users with remote perception, decision making and command generation (Fong & Thorpe, 2001). A controller with support for shared control also needs to correctly identify the user's intention and choose adequate control policy. Several studies have addressed intention recognition and policy selection in shared control applications. Works by Aigner and McCarragher (1997), Crandall and Goodrinch (2002), Kofman et al. (2005), Armbrust et al. (2010), Kim et al. (2012) and You and Hauser (2012) mainly focus on task arbitration while assuming that the robot knows the user's intention.

In the study by Kofman et al. (2005), a method to track a human's arm position and motion is proposed. It uses stereo cameras such that a 3D image is constructed by obtaining 2D image coordinates of the hand-arm positions. The constructed 3D image is processed and control commands are generated in real time to manipulate a 6 DoF robot and end-effector, thereby replicating the human's hand motions. Their method focus on motion replication and no behavior or intention recognition is developed.

In the work by Armbrust et al. (2010), a behavior-based approach to integrate direct teleoperation and semi-autonomous robot control modes is proposed in order to provide different autonomy levels in the off-road robot RAVON. The idea was to have one control system that is able to select control modes automatically using behavior fusion to reduce user interventions by accepting user commands and sending them to the safety system for collision detection. In case of no collision hazard, the system gradually takes over control and drives the robot.

Debus et al. (2001) conducted several experiments regarding undersea connector mating performed in the offshore oil industry. A shared control mechanism was developed to orient the connector automatically based on the socket orientation estimation, and send feedback to the operator to finalize the insertion.

Many other works strive for user's intent recognition for better shared control by fixating the number of predefined behaviors the robot is able to perform. Therefore, a behavior matching mechanism is applied to pick the one that best matches user intent from the robot's repertoire. Works by Li and Okamura (2003), Fagg et al. (2004), Aarno et al. (2005), Yu et al. (2005), Nielsen et al. (2006) and Bussy et al. (2012) are worth mentioning. In the study by Li and Okamura (2003), a system for human-machine cooperation that addresses how and when to assist a human using continuous HMM training is proposed. The system is able to recognize human intents in real time by computing probabilities of the executed motion sequence and create network for real time continuous HMM recognition and select the sequence with the highest likelihood.

Fagg et al. (2004) proposed a method to predict user intents by observing teleoperated robot movements over an object. They used a vision system to extract various features of the observed object like shape, size and color and translate them into control parameters that are associated to reach-to-grasp motions. Then, the likelihood of the predicted actions with the received commands is measured to form hypotheses. The level of likelihood for all possible actions are shown in a 3D display where the user can see which hypothesis has the highest likelihood and which robot motion is selected by the system. The display allows the user to view the selected hypothesis and confirm the movement by a hand gesture before handing over the control to the robot.

In the work by Bussy et al. (2012), a complete control scheme to perform complex transportation tasks in collaboration with humans is introduced. In order to accomplish the transportation task, the robot must be able to predict the human's intended trajectory and switch the role from follower to leader. Their approach is to decompose the motions lead by the human into predefined motion primitives and use a finite state machine to describe possible sequences of primitives. Therefore, a trajectory planner reactively generates appropriate sequences of motions according to the current movements for both follower and leader modes.

In contrast to many real-world scenarios, some of the mentioned studies assume

that environment and the objects of attention do not change significantly. Dragnan and Srinivasa (2013) proposed a formalism for shared control based on machine learning, control theory and concepts of human-robot interaction to address both mentioned challenges in a changing environment. Their prediction method is based on inverse reinforcement learning that assists the robot with accurate predictions from motion while a GUI and speech interface is used to specify the user's intentions.

Several techniques have been used to communicate user intention to the robot. In the study by Hoppenot and Colle (2001), a control station comprised of a control device (e.g. joystick) and a screen to display robot position together with images perceived by the robot enhanced with augmented reality techniques was used. The control station was mainly designed for a handicapped individual to control and manipulate a robotic arm mounted on a mobile platform. A work by Graf et al. (2004) uses speech commands and a GUI displayed on an integrated touch screen to provide user intentions. Once the commands provided, a symbolic planner uses SQL statements to generate a list of possible behaviors. The most suitable behavior is picked from the list and executed while the user has the option to interrupt or cancel the whole task. In another study by Blev et al. (2004), mimic recognition and facial expressions are applied to notify the robot about the user's intention. Speech recognition can be used to specify the intent to the robot as described by Volosyak et al. (2005). Dune et al. (2007) proposed a one-click approach to communicate user's intention with a MANUS arm mounted on a wheelchair. An "eye-in-hand" camera is mounted on the gripper and an "eye-to-hand" camera is mounted on top of the wheelchair. The eve-to-hand camera provides large view of the scene and once the user clicks on its view, a grasping action of the object of attention is performed. The object of attention is determined based on the images acquired by both cameras and processed by epipolar geometry and Bayesian enforcement.

Some of the approaches mentioned above demand users to explicitly communicate their intents to the robot each time, and prior to accomplishing a task, while in our work (Fonooni & Hellström, d) a novel technique for behavior recognition combined with priming is used to implicitly communicate the user's intention, and thereby allowing the robot to select the corresponding behavior.

6.1 Shared Control for Learning from Demonstration

Despite many applications of shared control in assisting users with complex and exhausting tasks in unstructured environments, there are additional situations where it can play a key role. One of the domains where shared control is used to improve performance is in LfD (Li et al., 2006; Bodenstedt et al., 2012; Goil et al., 2013; Rafii-Tari et al., 2014). In the current thesis, our aim is to employ shared control to help users demonstrating behaviors in a more convenient manner. Instead of repeating a demonstration using direct teleoperation, a behavior recognition system combined with a shared control can be used to reduce the user's workload when

several demonstrations of the same behavior are needed. Since a mature shared control system has the ability to identify the user's intent, it can contribute to both low- and high-level learning of behaviors by providing necessary information regarding objects of attention and the purpose of demonstrations. Therefore, priming mechanisms can be used not only in the high-level learning methods, but also during teleoperation and before context formation. However, additional research is required to compare the outcome of our learning methods using shared control as stated above with direct teleoperation.

Chapter 7 Outlook

Current work can be extended in many directions based on the achievements in designing and implementing an architecture for robot's imitation learning including methods for high-level learning and control. There are known limitations to our learning methods that make them inefficient under certain circumstances. Extension of current learning methods to employ all abilities of Semantic Networks is of particular importance. This includes implementing a new type of inhibitory links to represent negations.

In many situations where ignoring elements of demonstrations is simpler or more time efficient, negative priming (Tipper, 1985) can help to disperse robot's attention to lose focus on irrelevant elements. Such a situation can be when the robot is equipped with various sensors and perceive many objects and features of the environment.

Currently, our system heavily depends on the information given in the core SN that significantly affects the learning outcomes if insufficient or incorrect information is provided. Heading toward self-organizing systems where the robot learns new skills based on its interaction with the world and other agents and without *a priori* knowledge, is a huge leap forward. In such systems, the robot needs to have self-exploration capabilities, ability to alter itself based on its experiences, and anticipation skills to interact better with the world (Pfeifer et al., 2007).

Another research direction is to develop a response facilitation process and employ it to identify, imitate and predict the action of others (Kopp & Graeser, 2006). The robot observes the tutor actions and continuously compares them with its own repertoire to predict the next movements. If the action is identified, it will be immediately performed by the robot and in case of no matching, it switches to the learning mode to add the newly observed action to its repertoire.

Finally, developing a learning method based on implicit imitation has several advantages compared to direct imitation learning (Price & Boutilier, 2003). The robot with the ability to learn through implicit imitation does not require any agent to act as a tutor and it learns a new skill by observing other agents performing the skill. This approach is very useful when the tutor is not able or willing to provide feedback to the robot, and it might need to observe several agents to acquire the

skill correctly.

Chapter 8 Contributions

The main contribution of this thesis is the introduction of novel methods for interactive learning and reproduction of high-level representation of behaviors within an architecture tailored for robot's imitation learning. The architecture involves learning methods with attention mechanisms based on Semantic Networks and spreading activation theory for identifying important elements of demonstrations as well as recognizing the tutor's intentions. Learning methods are capable of resolving certain types of ambiguity by utilizing priming mechanism as a bias prior to learning. Furthermore, integration of low- and high-level learning, techniques for sequence learning and reproduction of skills considering the tutor's intentions are described. The infrastructure has been employed for the purpose of behavior arbitration and reproduction. Finally, a shared control system combined with the visual servoing guided primitives, and a priming mechanism for better intention recognition is introduced.

8.1 Paper I

In this paper (Fonooni et al., 2012), a rudimentary architecture for learning highlevel representation of behaviors is introduced. The aim is to integrate Predictive Sequence Learning (PSL) as low-level learning and control mechanism with a highlevel controller that focuses on replicating demonstrated tasks with no knowledge about goals or intentions. The Novelty Detection technique with attentional mechanism based on semantic networks, spreading activation and statistical t-test is introduced.

The system is tested and evaluated with a scenario, in which the goal is to push a movable object towards a designated area. While the task is demonstrated with a certain object, with its particular features, the system is able to generalize, and reproduce the task by observing different, but similar, types of objects. Thereby, the proposed architecture and Novelty Detection are shown to be suitable for learning and generalizing object affordances. Reproduction of learned behaviors is engaged by exploring the environment and observing any related object. Therefore, stimulus enhancement is applied as a mechanism to trigger behaviors in the robot's repertoire.

8.2 Paper II

In the second paper (Fonooni et al., 2013), general challenges of LfD at both lowand high levels are investigated. Several improvements are made to the architecture, with the aim of facilitating intention recognition and goal emulation. In the developed architecture, PSL is replaced by hard-coded action-primitive pairs that do not require learning. The Multiple Demonstrations technique that uses one-way ANOVA test and spreading activation theory is presented. The attention mechanism with the same impact on learning behaviors as presented in the first paper, is applied with the slight changes in the way relevant information is detected in demonstrations. The goal management module with goal creation and inference capabilities is added. Motivating the robot to exhibit a previously learned behavior with the priming mechanism is elaborated. The whole architecture showed to be efficient for sequence learning and reproduction, by decomposing sequences into sub-behaviors that are associated to action-primitive pairs.

Finally, an Urban Search and Rescue (USAR) scenario is defined to evaluate the applicability of the proposed architecture and the learning method. The goal is to assist a human agent to uncover a victim from a pile of rubble in an environment damaged by an earthquake. Results show the system's ability in learning and reproduction of such complex tasks.

8.3 Paper III

The third paper (Fonooni et al., a), attempts to answer the questions "What to imitate?" and "When to imitate?", by extending the Multiple Demonstrations technique introduced in the second paper. This technique has practical limitations that prevent the robot to correctly determine what elements of demonstration are most important. The one-way ANOVA test is replaced by ant colony optimization algorithms and thus Ant System (AS) and Ant Colony System (ACS) have been utilized. The main contribution of the paper is to investigate the applicability of AS and ACS for identification of relevant nodes, and thereby improving the context formation process. Moreover, generalization of concepts by means of spreading activation and ant colony optimization algorithms is investigated.

Although low-level learning and control is not directly addressed, the proposed method can be applied with both PSL and action-primitive pairs.

The whole learning and reproduction mechanisms is tested in a scenario in which the robot learns to identify cylindrical, square and triangular shapes and put them in their respective baskets. Results show that both the AS and ACS algorithms prove to be powerful alternatives to the previously developed Multiple Demonstrations techniques combined with one-way ANOVA test.

8.4 Paper IV

In the fourth paper (Kozlov et al., 2013), a field robotic assistant for USAR application is developed to put our architecture to test. The work integrates high-level behavior learning and reproduction with low-level robotic arm manipulation and autonomous robot navigation. The robot sequentially learned necessary high-level behaviors with the Multiple Demonstrations method described in paper II (Fonooni et al., 2013). The tutor created sub-behaviors and goals as explained in the aforementioned paper by demonstrating each sub-behavior and its corresponding action. The low-level controller used action-primitive pairs where all the primitives were learned using motor babbling. Motor babbling provided inverse kinematic model of the robotic arm that is used to perform grasping and depositing actions. The results of using the robot in a quarry for assisting in a rubble clearing task implies the capabilities of the architecture in motivating the robot using the high-level controller and perform the delegated task using the low-level controller.

8.5 Paper V

The fifth paper (Fonooni et al., b) investigates the nature of ambiguity involved in inferring the tutor's intents when the demonstrations map to several intentions. The aim is to suggest a learning method that resolves this type of ambiguity with a reasonable speed and adequate result. Therefore, a priming mechanism and a model of human memory are used to bias the robot prior to learning. The Multiple Demonstrations method combined with Ant System algorithm is used to form contexts. The method is then evaluated in a scenario in which the tutor's intention was not clearly described and typically, several demonstrations would have been needed to form contexts correctly.

Based on the conducted experiments, priming together with an attentional mechanism built on the Ant System algorithm showed significant improvements in both learning speed and intention recognition compared to no priming as described in Paper III (Fonooni et al., a). The Priming mechanism improved reasoning about what aspects of a demonstration demand the robot's attention by eliminating irrelevant elements and providing one-shot learning.

8.6 Paper VI

In the sixth paper (Fonooni & Hellström, c), two vision-based approaches for robot control using visual servoing are compared both analytically and numerically. The first approach is Image Based visual Servoing (IBVS), which has its roots in traditional control theory. The second approach is Behavior Based Visual Servoing (BBVS) that applies principles of behavior-based robotics. The two approaches are evaluated with a picking task performed by a 3 DoF robotic arm. The results indicate several similarities between both approaches while BBVS showed significantly better performance. The main application of the visual servoing in the current thesis is to have another alternative for implementation of primitives. This approach has appealing compatibility with the rest of the architecture and is further used in our shared control system described in Paper VII (Fonooni & Hellström, d).

8.7 Paper VII

In the seventh paper (Fonooni & Hellström, d), we strive for developing a shared control system with enhanced intention recognition capabilities to support teleoperation tasks. The main contribution of this work is to integrate shared control with the priming mechanism for improved user intent identification and thereby better behavior recognition. The proposed system is intended to be used instead of direct teleoperation during behavior demonstrations in LfD while it also has potential to be useful as a standalone shared control interface.

The developed solution is tested with an object collection task in which the robot and user are cooperating. The experiments showed that the priming mechanism successfully biased the robot to identify user's intention correctly, and reduced the direct teleoperation time.

Bibliography

- Aarno, D., Ekvall, S., & Kragic, D. (2005). Adaptive virtual fixtures for machineassisted teleoperation tasks. In *Robotics and Automation*, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on (pp. 1139–1144).: IEEE.
- Aigner, P. & McCarragher, B. (1997). Human integration into robot control utilising potential fields. In *Robotics and Automation*, 1997. Proceedings., 1997 IEEE International Conference on, volume 1 (pp. 291–296).: IEEE.
- Alissandrakis, A., Nehaniv, C. L., & Dautenhahn, K. (2002). Imitation with alice: Learning to imitate corresponding actions across dissimilar embodiments. Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 32(4), 482–496.
- Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. *Psychological review*, 111(4), 1036– 1060.
- Anelli, F., Nicoletti, R., Kalkan, S., Sahin, E., & Borghi, A. M. (2012). Human and robotics hands grasping danger. In *Neural Networks (IJCNN)*, *The 2012 International Joint Conference on* (pp. 1–8).: IEEE.
- Argall, B. D., Chernova, S., Veloso, M., & Browning, B. (2009). A survey of robot learning from demonstration. *Robotics and Autonomous Systems*, 57(5), 469–483.
- Armbrust, C., Proetzsch, M., Schäfer, B.-H., & Berns, K. (2010). A behaviourbased integration of fully autonomous, semi-autonomous, and tele-operated control modes for an off-road robot. In *Proceedings of the 2nd IFAC Symposium on Telematics Applications, Timisoara, Romania.*
- Bandera, J., Rodríguez, J., Molina-Tanco, L., & Bandera, A. (2012). A survey of vision-based architectures for robot learning by imitation. *International Journal* of Humanoid Robotics, 9(1).
- Bekey, G. A. (2005). Autonomous robots: from biological inspiration to implementation and control. MIT press.

- Bensch, S. & Hellström, T. (2010). On ambiguity in robot learning from demonstration. (pp. 47–56).
- Billard, A., Calinon, S., Dillmann, R., & Schaal, S. (2008). Handbook of robotics chapter 59: Robot programming by demonstration.
- Billard, A. & Hayes, G. (1999). Drama, a connectionist architecture for control and learning in autonomous robots. *Adaptive Behavior*, 7(1), 35–63.
- Billing, E., Hellström, T., & Janlert, L.-E. (2012). Robot learning from demonstration using predictive sequence learning. *Intech Robotic Systems-Applications*, *Control and Programming*, Dr. Ashish Dutta (Ed.).
- Billing, E. A. & Hellström, T. (2010). A formalism for learning from demonstration. Paladyn Journal of Behavioral Robotics, 1(1), 1–13.
- Billing, E. A., Hellstroöm, T., & Janlert, L.-E. (2010). Behavior recognition for learning from demonstration. In *Robotics and Automation (ICRA)*, 2010 IEEE International Conference on (pp. 866–872).: IEEE.
- Bley, F., Rous, M., Canzler, U., & Kraiss, K.-F. (2004). Supervised navigation and manipulation for impaired wheelchair users. In Systems, Man and Cybernetics, 2004 IEEE International Conference on, volume 3 (pp. 2790–2796).: IEEE.
- Bodenstedt, S., Padoy, N., & Hager, G. D. (2012). Learned partial automation for shared control in tele-robotic manipulation. In AAAI Fall Symposium: Robots Learning Interactively from Human Teachers (pp. 10–15).
- Brass, M. & Heyes, C. (2005). Imitation: is cognitive neuroscience solving the correspondence problem? *Trends in cognitive sciences*, 9(10), 489–495.
- Breazeal, C. (2009). Role of expressive behaviour for robots that learn from people. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1535), 3527–3538.
- Breazeal, C., Berlin, M., Brooks, A., Gray, J., & Thomaz, A. L. (2006). Using perspective taking to learn from ambiguous demonstrations. *Robotics and Au*tonomous Systems, 54(5), 385–393.
- Breazeal, C. & Scassellati, B. (1999). A context-dependent attention system for a social robot. (pp. 1146–1151).
- Breazeal, C. & Scassellati, B. (2002a). Challenges in building robots that imitate people. *Imitation in animals and artifacts*, (pp. 363–390).
- Breazeal, C. & Scassellati, B. (2002b). Robots that imitate humans. Trends in Cognitive Sciences, 6(11), 481–487.
- Brown, A. S. (1996). Single and multiple test repetition priming in implicit memory. Memory, 4(2), 159–174.

- Buchsbaum, D. & Blumberg, B. (2005). Imitation as a first step to social learning in synthetic characters: a graph-based approach. In *Proceedings of the 2005* ACM SIGGRAPH/Eurographics symposium on Computer animation (pp. 9–18).: ACM.
- Bussy, A., Gergondet, P., Kheddar, A., Keith, F., & Crosnier, A. (2012). Proactive behavior of a humanoid robot in a haptic transportation task with a human partner. In *RO-MAN*, 2012 IEEE (pp. 962–967).: IEEE.
- Byrne, R. W., Russon, A. E., et al. (1998). Learning by imitation: a hierarchical approach. *Behavioral and brain sciences*, 21(5), 667–684.
- Cakmak, M., DePalma, N., Arriaga, R., & Thomaz, A. L. (2009). Computational benefits of social learning mechanisms: Stimulus enhancement and emulation. In *Development and Learning*, 2009. ICDL 2009. IEEE 8th International Conference on (pp. 1–7).: IEEE.
- Cakmak, M. & Thomaz, A. L. (2012). Designing robot learners that ask good questions. In Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction (pp. 17–24).: ACM.
- Calinon, S. & Billard, A. (2007). Incremental learning of gestures by imitation in a humanoid robot. In *Proceedings of the ACM/IEEE international conference on Human-robot interaction* (pp. 255–262).: ACM.
- Calinon, S., Guenter, F., & Billard, A. (2007). On learning, representing, and generalizing a task in a humanoid robot. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 37(2), 286–298.
- Call, J. & Carpenter, M. (2002). Three sources of information in social learning. *Imitation in animals and artifacts*, (pp. 211–228).
- Carlos Fernando Morales, O. & Fernando De la Rosa, R. (2013). Ambiguity analysis in learning from demonstration applications for mobile robots. In Advanced Robotics (ICAR), 2013 16th International Conference on (pp. 1–6).: IEEE.
- Cederborg, T. & Oudeyer, P.-Y. (2013). From language to motor gavagai: Unified imitation learning of multiple linguistic and nonlinguistic sensorimotor skills. Autonomous Mental Development, IEEE Transactions on, 5(3), 222–239.
- Cederborg, T. & Oudeyer, P.-Y. (2014). A social learning formalism for learners trying to figure out what a teacher wants them to do. *Paladyn, Journal of Behavioral Robotics*, 5(1).
- Chao, C., Cakmak, M., & Thomaz, A. L. (2011). Towards grounding concepts for transfer in goal learning from demonstration. In *Development and Learning* (*ICDL*), 2011 IEEE International Conference on, volume 2 (pp. 1–6).: IEEE.
- Chella, A., Dindo, H., & Infantino, I. (2006). A cognitive framework for imitation learning. *Robotics and Autonomous Systems*, 54(5), 403–408.

- Chernova, S. & Veloso, M. (2008). Learning equivalent action choices from demonstration. In Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on (pp. 1216–1221).: IEEE.
- Chersi, F. (2012). Learning through imitation: a biological approach to robotics. Transactions on Autonomous Mental Development, 4(3), 204–214.
- Clegg, B. A., DiGirolamo, G. J., & Keele, S. W. (1998). Sequence learning. Trends in Cognitive Sciences, 2(8), 275–281.
- Collins, A. M. & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological review*, 82(6), 407–428.
- Collins, A. M. & Quillian, M. R. (1969). Retrieval time from semantic memory. Journal of verbal learning and verbal behavior, 8(2), 240–247.
- Crandall, J. W. & Goodrich, M. A. (2002). Characterizing efficiency of human robot interaction: A case study of shared-control teleoperation. In *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, volume 2 (pp. 1290–1295).: IEEE.
- Crestani, F. (1997). Application of spreading activation techniques in information retrieval. *Artificial Intelligence Review*, 11(6), 453–482.
- Cubek, R. & Ertel, W. (2012). Conceptual similarity as a key to high-level robot programming by demonstration. In *Robotics; Proceedings of ROBOTIK 2012;* 7th German Conference on (pp. 1–6).: VDE.
- Dalgalarrondo, A., Dufourd, D., & Filliat, D. (2004). Controlling the autonomy of a reconnaissance robot. In *Defense and Security* (pp. 314–325).: International Society for Optics and Photonics.
- Dautenhahn, K. & Nehaniv, C. L. (2002). The agent-based perspective on imitation. MIT Press.
- Debus, T., Stoll, J., Howe, R. D., & Dupont, P. (2001). Cooperative human and machine perception in teleoperated assembly. In *Experimental Robotics VII* (pp. 51–60). Springer.
- Demiris, J. & Hayes, G. (2002). Imitation as a dual-route process featuring predictive and learning components; a biologically plausible computational model. *Imitation in animals and artifacts*, (pp. 327–361).
- Demiris, Y. & Dearden, A. (2005). From motor babbling to hierarchical learning by imitation: a robot developmental pathway. (pp. 31–37).
- Demiris, Y. & Khadhouri, B. (2006). Hierarchical attentive multiple models for execution and recognition of actions. *Robotics and autonomous systems*, 54(5), 361–369.
- Dillmann, R. (2004). Teaching and learning of robot tasks via observation of human performance. *Robotics and Autonomous Systems*, 47(2), 109–116.

- Dogar, M. R., Cakmak, M., Ugur, E., & Sahin, E. (2007). From primitive behaviors to goal-directed behavior using affordances. In *Intelligent Robots and Systems*, 2007. IROS 2007. IEEE/RSJ International Conference on (pp. 729–734).: IEEE.
- Dorigo, M., Birattari, M., & Stützle, T. (2006). Ant colony optimization artificial ants as a computational intelligence technique. *IEEE Computational Intelligence Magazine*, 1(4), 28–39.
- Dorigo, M. & Gambardella, L. M. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. *Evolutionary Computation*, *IEEE Transactions on*, 1(1), 53–66.
- Dragan, A. D. & Srinivasa, S. S. (2013). A policy-blending formalism for shared control. The International Journal of Robotics Research, 32(7), 790–805.
- Dune, C., Leroux, C., & Marchand, E. (2007). Intuitive human interaction with an arm robot for severely handicapped people-a one click approach. In *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on* (pp. 582– 589).: IEEE.
- Ekvall, S. & Kragic, D. (2005). Grasp recognition for programming by demonstration. In Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on (pp. 748–753).: IEEE.
- Erlhagen, W., Mukovskiy, A., Bicho, E., Panin, G., Kiss, C., Knoll, A., Van Schie, H., & Bekkering, H. (2006). Goal-directed imitation for robots: A bio-inspired approach to action understanding and skill learning. *Robotics and autonomous* systems, 54(5), 353–360.
- Fagg, A. H., Rosenstein, M., Platt, R., & Grupen, R. A. (2004). Extracting user intent in mixed initiative teleoperator control. In Proc. American Institute of Aeronautics and Astronautics Intelligent Systems Technical Conference.
- Flavell, J. H., Beilin, H., & Pufall, P. (1992). Perspectives on perspective-taking. *Piagets theory: Prospects and possibilities*, (pp. 107–139).
- Fong, T. & Thorpe, C. (2001). Vehicle teleoperation interfaces. Autonomous robots, 11(1), 9–18.
- Fong, T., Thorpe, C., & Baur, C. (2001). A safeguarded teleoperation controller. In IEEE International Conference on Advanced Robotics (ICAR), number LSRO2-CONF-2001-002.
- Fonooni, B. & Hellström, T. (c). On the similarities between control based and behavior based visual servoing. In 2015 ACM/SIGAPP Symposium On Applied Computing (SAC), (in press).
- Fonooni, B. & Hellström, T. (d). Applying a priming mechanism for intention recognition in shared control. In 2015 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), (in press).

- Fonooni, B., Hellström, T., & Janlert, L.-E. (2012). Learning high-level behaviors from demonstration through semantic networks. In *Proceedings of 4th International Conference on Agents and Artificial Intelligence* (pp. 419–426).
- Fonooni, B., Hellström, T., & Janlert, L.-E. (2013). Towards goal based architecture design for learning high-level representation of behaviors from demonstration. In 2013 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA) (pp. 67–74).
- Fonooni, B., Hellström, T., & Janlert, L.-E. (b). Priming as a means to reduce ambiguity in learning from demonstration. *International Journal of Social Robotics*, (submitted).
- Fonooni, B., Jevtić, A., Hellström, T., & Janlert, L.-E. (a). Applying ant colony optimization algorithms for high-level behavior learning and reproduction from demonstrations. *Robotics and Autonomous Systems, (in press).*
- Friesen, A. L. & Rao, R. P. (2010). Imitation learning with hierarchical actions. In Development and Learning (ICDL), 2010 IEEE 9th International Conference on (pp. 263–268).: IEEE.
- Fukano, R., Kuniyoshi, Y., & Nagakubo, A. (2006). A cognitive architecture for flexible imitative interaction using tools and objects. In *Humanoid Robots*, 2006 6th IEEE-RAS International Conference on (pp. 376–381).: IEEE.
- Gibson, J. J. (1979). The ecological approach to visual perception. Houghton Mifflin.
- Gienger, M., Muhlig, M., & Steil, J. J. (2010). Imitating object movement skills with robots - a task-level approach exploiting generalization and invariance. In *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on* (pp. 1262–1269).: IEEE.
- Goil, A., Derry, M., & Argall, B. D. (2013). Using machine learning to blend human and robot controls for assisted wheelchair navigation. In *IEEE International Conference on Rehabilitation Robotics (ICORR)* (pp. 1–6).
- Goodrich, M. A., Crandall, J. W., & Stimpson, J. L. (2003). Neglect tolerant teaming: Issues and dilemmas. In Proceedings of the 2003 AAAI Spring Symposium on Human Interaction with Autonomous Systems in Complex Environments.
- Graf, B., Hans, M., & Schraft, R. D. (2004). Care-o-bot ii-development of a next generation robotic home assistant. Autonomous robots, 16(2), 193–205.
- Gärdenfors, P. (2000). Conceptual Spaces. MIT Press.
- Hajimirsadeghi, H., Ahmadabadi, M. N., Araabi, B. N., & Moradi, H. (2012). Conceptual imitation learning in a human-robot interaction paradigm. ACM Transactions on Intelligent Systems and Technology (TIST), 3(2), 28.
- Hasemann, J.-M. (1995). Robot control architectures: Application requirements, approaches, and technologies. In *Photonics East'95* (pp. 88–102).: International Society for Optics and Photonics.

- Hebb, D. O. (2002). The organization of behavior: A neuropsychological theory. Psychology Press.
- Henson, R. & Rugg, M. (2003). Neural response suppression, haemodynamic repetition effects, and behavioural priming. *Neuropsychologia*, 41(3), 263–270.
- Hoffman, M. W., Grimes, D. B., Shon, A. P., & Rao, R. P. (2006). A probabilistic model of gaze imitation and shared attention. *Neural Networks*, 19(3), 299–310.
- Hoppenot, P. & Colle, E. (2001). Localization and control of a rehabilitation mobile robot by close human-machine cooperation. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 9(2), 181–190.
- Howell, D. C. (2011). Statistical methods for psychology. Cengage Learning.
- Huber, D. E. (2008). Immediate priming and cognitive aftereffects. Journal of Experimental Psychology: General, 137(2), 324–347.
- Iacoboni, M. (2009). Imitation, empathy, and mirror neurons. Annual review of psychology, 60, 653–670.
- Ijspeert, A. J., Nakanishi, J., Hoffmann, H., Pastor, P., & Schaal, S. (2013). Dynamical movement primitives: learning attractor models for motor behaviors. *Neural computation*, 25(2), 328–373.
- Jansen, B. & Belpaeme, T. (2006). A computational model of intention reading in imitation. Robotics and Autonomous Systems, 54(5), 394–402.
- Jevtić, A., Lucet, E., Kozlov, A., & Gancet, J. (2012). Intro: A multidisciplinary approach to intelligent human-robot interaction. In World Automation Congress (WAC), 2012 (pp. 1–6).: IEEE.
- Kim, D.-J., Hazlett-Knudsen, R., Culver-Godfrey, H., Rucks, G., Cunningham, T., Portee, D., Bricout, J., Wang, Z., & Behal, A. (2012). How autonomy impacts performance and satisfaction: Results from a study with spinal cord injured subjects using an assistive robot. Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 42(1), 2–14.
- Kofman, J., Wu, X., Luu, T. J., & Verma, S. (2005). Teleoperation of a robot manipulator using a vision-based human-robot interface. *Industrial Electronics*, *IEEE Transactions on*, 52(5), 1206–1219.
- Kopp, S. & Graeser, O. (2006). Imitation learning and response facilitation in embodied agents. In *Intelligent Virtual Agents* (pp. 28–41).: Springer.
- Kozlov, A., Gancet, J., Letier, P., Schillaci, G., Hafner, V. V., Fonooni, B., Nevatia, Y., & Hellstrom, T. (2013). Development of a search and rescue field robotic assistant. In Safety, Security, and Rescue Robotics (SSRR), 2013 IEEE International Symposium on (pp. 1–5).: IEEE.
- Kragic, D., Christensen, H. I., et al. (2002). Survey on visual servoing for manipulation. Computational Vision and Active Perception Laboratory, 15.

- Laird, J. E. (2008). Extending the soar cognitive architecture. Frontiers in Artificial Intelligence and Applications, 171, 224–235.
- Langley, P., Laird, J. E., & Rogers, S. (2009). Cognitive architectures: Research issues and challenges. *Cognitive Systems Research*, 10(2), 141–160.
- Lee, K. & Demiris, Y. (2011). Towards incremental learning of task-dependent action sequences using probabilistic parsing. In *Development and Learning (ICDL)*, 2011 IEEE International Conference on, volume 2 (pp. 1–6).: IEEE.
- Lee, K. H., Lee, J., Thomaz, A. L., & Bobick, A. F. (2009). Effective robot task learning by focusing on task-relevant objects. In *Intelligent Robots and* Systems, 2009. IROS 2009. IEEE/RSJ International Conference on (pp. 2551– 2556).: IEEE.
- Li, M. & Okamura, A. M. (2003). Recognition of operator motions for real-time assistance using virtual fixtures. In *Haptic Interfaces for Virtual Environment* and *Teleoperator Systems*, 2003. *HAPTICS 2003. Proceedings. 11th Symposium* on (pp. 125–131).: IEEE.
- Li, Y., Patoglu, V., & OŠMalley, M. K. (2006). Shared control for training in virtual environments: Learning through demonstration. In *Proceedings of EuroHaptics* (pp. 93–99).
- Lopes, M., Melo, F. S., & Montesano, L. (2007). Affordance-based imitation learning in robots. In *Intelligent Robots and Systems*, 2007. IROS 2007. IEEE/RSJ International Conference on (pp. 1015–1021).: IEEE.
- Maccotta, L. & Buckner, R. (2004). Evidence for neural effects of repetition that directly correlate with behavioral priming. *Cognitive Neuroscience, Journal of*, 16(9), 1625–1632.
- Mahmoodian, M., Moradi, H., Ahmadabadi, M. N., & Araabi, B. N. (2013). Hierarchical concept learning based on functional similarity of actions. In *Robotics* and Mechatronics (ICRoM), 2013 First RSI/ISM International Conference on (pp. 1–6).: IEEE.
- Markou, M. & Singh, S. (2003). Novelty detection: a review part 1: statistical approaches. Signal processing, 83(12), 2481–2497.
- Mataric, M. J. (1997). Behaviour-based control: Examples from navigation, learning, and group behaviour. Journal of Experimental & Theoretical Artificial Intelligence, 9(2-3), 323–336.
- Mataric, M. J. (2002). Sensoryf: Linking perception to action and biology to robotics. In *Imitation in Animals and Artifacts* (pp. 391–422).: MIT Press.
- Maxfield, L. (1997). Attention and semantic priming: A review of prime task effects. *Consciousness and cognition*, 6(2), 204–218.

BIBLIOGRAPHY

- McNamara, T. P. (2004). Semantic priming: Perspectives from memory and word recognition. Psychology Press.
- Meltzoff, A. N. (1988). Imitation, objects, tools, and the rudiments of language in human ontogeny. *Human evolution*, 3(1-2), 45–64.
- Meltzoff, A. N. & Moore, M. K. (1997). Explaining facial imitation: A theoretical model. *Early Development & Parenting*, 6(3-4), 179–192.
- Miklósi, A. (1999). The ethological analysis of imitation. *Biological Reviews*, 74(3), 347–374.
- Mitchell, T. M., Keller, R. M., & Kedar-Cabelli, S. T. (1986). Explanation-based generalization: A unifying view. *Machine learning*, 1(1), 47–80.
- Montesano, L., Lopes, M., Bernardino, A., & Santos-Victor, J. (2008). Learning object affordances: from sensory-motor coordination to imitation. *Robotics*, *IEEE Transactions on*, 24(1), 15–26.
- Neely, J. H. (1977). Semantic priming and retrieval from lexical memory: Roles of inhibitionless spreading activation and limited-capacity attention. *Journal of experimental psychology: general*, 106(3), 226–254.
- Neely, J. H. (1991). Semantic priming effects in visual word recognition: A selective review of current findings and theories. *Basic processes in reading: Visual word* recognition, 11, 264–336.
- Nehaniv, C. L. & Dautenhahn, K. (2002). The correspondence problem. *Imitation in animals and artifacts*, (pp. 41–61).
- Nielsen, C. W., Bruemmer, D. J., Few, D. A., & Walton, M. (2006). Mixedinitiative interactions for mobile robot search. In American Association for Artificial Intelligence Mobile Robot Workshop, Boston, MA (pp. 25–29).
- Ochsner, K. N., Chiu, C.-Y. P., & Schacter, D. L. (1994). Varieties of priming. Current Opinion in Neurobiology, 4(2), 189–194.
- Pastor, P., Hoffmann, H., Asfour, T., & Schaal, S. (2009). Learning and generalization of motor skills by learning from demonstration. In *Robotics and Automation*, 2009. ICRA'09. IEEE International Conference on (pp. 763–768).: IEEE.
- Pfeifer, R., Lungarella, M., & Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. *science*, 318(5853), 1088–1093.
- Price, B. & Boutilier, C. (2003). Accelerating reinforcement learning through implicit imitation. J. artif. intell. res. (jair), 19, 569–629.
- Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J., Wheeler, R., & Ng, A. Y. (2009). Ros: an open-source robot operating system. In *ICRA* workshop on open source software, volume 3.

- Rafii-Tari, H., Liu, J., Payne, C. J., Bicknell, C., & Yang, G.-Z. (2014). Hierarchical hmm based learning of navigation primitives for cooperative robotic endovascular catheterization. In *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2014* (pp. 496–503). Springer.
- Rips, L. J., Shoben, E. J., & Smith, E. E. (1973). Semantic distance and the verification of semantic relations. *Journal of verbal learning and verbal behavior*, 12(1), 1–20.
- Rogers, T. (2008). Computational models of semantic memory. The Cambridge handbook of computational psychology, (pp. 226–266).
- Sallé, D., Traonmilin, M., Canou, J., & Dupourqué, V. (2007). Using microsoft robotics studio for the design of generic robotics controllers: the robubox software. In ICRA 2007 Workshop Software Development and Integration in Robotics - "Understanding Robot Software Architectures", Roma, Italy.
- Scassellati, B. (1999a). Imitation and mechanisms of joint attention: A developmental structure for building social skills on a humanoid robot. In *Computation* for metaphors, analogy, and agents (pp. 176–195). Springer.
- Scassellati, B. (1999b). Knowing what to imitate and knowing when you succeed. In Proceedings of the AISBŠ99 Symposium on Imitation in Animals and Artifacts (pp. 105–113).
- Schaal, S. (1999). Is imitation learning the route to humanoid robots? Trends in cognitive sciences, 3(6), 233–242.
- Scheutz, M. (2002). Affective action selection and behavior arbitration for autonomous robots. In Proceedings of the International Conference on Artificial Intelligence (ICAI), volume 1 (pp. 334–340).
- Sheridan, T. B. (1995). Teleoperation, telerobotics and telepresence: A progress report. Control Engineering Practice, 3(2), 205–214.
- Skoglund, A., Iliev, B., & Palm, R. (2010). Programming-by-demonstration of reaching motions-a next-state-planner approach. *Robotics and Autonomous Sys*tems, 58(5), 607–621.
- Sun, R. & Giles, C. L. (2001). Sequence learning: From recognition and prediction to sequential decision making. *IEEE Intelligent Systems*, 16(4), 67–70.
- Tan, H. (2012). Implementation of a framework for imitation learning on a humanoid robot using a cognitive architecture. The Future of Humanoid Robots: Research and Applications, (pp. 189–210).
- Taylor, M. E., Suay, H. B., & Chernova, S. (2011). Integrating reinforcement learning with human demonstrations of varying ability. In *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2* (pp. 617–624).: International Foundation for Autonomous Agents and Multiagent Systems.

- Thomaz, A. L. & Cakmak, M. (2009). Learning about objects with human teachers. In Proceedings of the 4th ACM/IEEE international conference on Human robot interaction (pp. 15–22).: ACM.
- Tipper, S. P. (1985). The negative priming effect: Inhibitory priming by ignored objects. The Quarterly Journal of Experimental Psychology, 37(4), 571–590.
- Tulving, E. (1972). Episodic and semantic memory. Organization of memory, (pp. 381–402).
- Tulving, E. & Schacter, D. L. (1990). Priming and human memory systems. Science, 247(4940), 301–306.
- Tversky, B., Lee, P., & Mainwaring, S. (1999). Why do speakers mix perspectives? Spatial cognition and computation, 1(4), 399–412.
- Vaidya, C. J., Gabrieli, J. D., Monti, L. A., Tinklenberg, J. R., & Yesavage, J. A. (1999). Dissociation between two forms of conceptual priming in alzheimer's disease. *Neuropsychology*, 13(4), 516–524.
- Vakanski, A., Mantegh, I., Irish, A., & Janabi-Sharifi, F. (2012). Trajectory learning for robot programming by demonstration using hidden markov model and dynamic time warping. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 42(4), 1039–1052.
- Vernon, D., Metta, G., & Sandini, G. (2007). A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents. *Evolutionary Computation, IEEE Transactions on*, 11(2), 151–180.
- Volosyak, I., Ivlev, O., & Graser, A. (2005). Rehabilitation robot friend ii-the general concept and current implementation. In *Rehabilitation Robotics*, 2005. *ICORR* 2005. 9th International Conference on (pp. 540–544).: IEEE.
- Warnier, M., Guitton, J., Lemaignan, S., & Alami, R. (2012). When the robot puts itself in your shoes. managing and exploiting human and robot beliefs. In *RO-MAN*, 2012 IEEE (pp. 948–954).: IEEE.
- Wig, G. S. (2012). Repetition suppression and repetition priming are processing outcomes. *Cognitive neuroscience*, 3(3-4), 247–248.
- Wiggs, C. L. & Martin, A. (1998). Properties and mechanisms of perceptual priming. Current opinion in neurobiology, 8(2), 227–233.
- You, E. & Hauser, K. (2012). Assisted teleoperation strategies for aggressively controlling a robot arm with 2d input. In *Robotics: Science and Systems*, volume 7 (pp. 354–361).
- Yu, W., Alqasemi, R., Dubey, R., & Pernalete, N. (2005). Telemanipulation assistance based on motion intention recognition. In *Robotics and Automation*, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on (pp. 1121–1126).: IEEE.

Zentall, T. R. (2001). Imitation in animals: evidence, function, and mechanisms. Cybernetics & Systems, 32(1-2), 53–96.



Department of Computing Science Umeå University, 901 87 Umeå, Sweden www.cs.umu.se ISBN 978-91-7601-189-8 ISSN 0348-0542 UMINF: 14.23