



Wilhelm Richert

Learning and imitation in heterogeneous robot groups

C-LAB Publication

Band 31

Wilhelm Richert

**Learning and imitation in
heterogeneous robot groups**



D 466 (Diss. Universität Paderborn)

Shaker Verlag
Aachen 2010

Bibliographic information published by the Deutsche Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available in the Internet at <http://dnb.d-nb.de>.

Zugl.: Paderborn, Univ., Diss., 2009

Copyright Shaker Verlag 2010

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording or otherwise, without the prior permission of the publishers.

Printed in Germany.

ISBN 978-3-8322-8874-7
ISSN 1438-3527

Shaker Verlag GmbH • P.O. BOX 101818 • D-52018 Aachen
Phone: 0049/2407/9596-0 • Telefax: 0049/2407/9596-9
Internet: www.shaker.de • e-mail: info@shaker.de

Richert

Learning and imitation in heterogeneous robot groups

C-LAB Publication

Herausgegeben von
Published by

Dr. Wolfgang Kern, Siemens AG
Prof. Dr. Franz-Josef Rammig, Universität Paderborn

Das C-LAB - Cooperative Computing & Communication Laboratory - leistet Forschungs- und Entwicklungsarbeiten und gewährleistet deren Transfer an den Markt. Es wurde 1985 von den Partnern Nixdorf Computer AG (nun Siemens AG) und der Universität Paderborn im Einvernehmen mit dem Land Nordrhein-Westfalen gegründet.

Die Vision, die dem C-LAB zugrunde liegt, geht davon aus, daß die gewaltigen Herausforderungen beim Übergang in die kommende Informations- und Wissensgesellschaft nur durch globale Kooperation und in tiefer Verzahnung von Theorie und Praxis gelöst werden können. Im C-LAB arbeiten deshalb Mitarbeiter von Hochschule und Industrie unter einem Dach in einer gemeinsamen Organisation an gemeinsamen Projekten mit internationalen Partnern eng zusammen.

C-LAB - the Cooperative Computing & Cooperation Laboratory - works in the area of research and development and safeguards its transfer into the market. It was founded in 1985 by Nixdorf Computer AG (now Siemens AG) and the University of Paderborn under the auspices of the State of North-Rhine Westphalia.

C-LAB's vision is based on the fundamental premise that the gargantuan challenges thrown up by the transition to a future information and knowledge society can only be met through global cooperation and deep interworking of theory and practice. This is why, under one roof, staff from the university and from industry cooperate closely on joint projects within a common research and development organization together with international partners. In doing so, C-LAB concentrates on those innovative subject areas in which cooperation is expected to bear particular fruit for the partners and their general well-being.



University of Paderborn

Learning and imitation in heterogeneous robot groups

Wilhelm Richert

Dissertation
in Computer Science

submitted to the

**Faculty of Electrical Engineering,
Computer Science, and Mathematics**

in partial fulfillment of the requirements for the degree of

**doctor rerum naturalium
(Dr. rer. nat.)**

Paderborn, 2009

Supervisors:

Prof. Dr. Franz J. Rammig, University of Paderborn

Prof. Dr. Hans Kleine Büning, University of Paderborn

Prof. Dr. Uwe Brinkschulte, University of Frankfurt

Date of public examination: 22. December 2009

Acknowledgements

First of all, I would like to thank my supervisor Prof. Dr. Franz Rammig for his guidance and constructive feedback. I also thank Prof. Dr. Hans Kleine Büning and Prof. Dr. Uwe Brinkschulte for vice-supervising my thesis, as well as Prof. Dr. Friedhelm Meyer auf der Heide, Prof. Dr. Achim Rettberg and Dr. Matthias Fischer for reviewing my work.

This work would not have been possible without the many fruitful discussions with and suggestions from my group leader Dr. Bernd Kleinjohann and my colleagues Dr. Lisa Kleinjohann, Dr. Dirk Stichling, Dr. Christian Reimann, Mr. Markus Koch, Claudius Stern, Philipp Adelt, and Andreas Thuy. I am especially grateful to Dr. Natascha Esau for her guidance in expressing my ideas as concise mathematical formulas.

Neither would this work have been possible without the bright students I had the opportunity to work with and who contributed to this work: Oliver Niehörster, Raphael Golombek, Ulrich Scheller, and Riccardo Tornese. I also wish to thank Marina Scheiderbauer and my brother Johann Richert for revising the English of my manuscript.

Last but not least, I heartily thank my wife Natalie for her patience and support as well as our two little sons Linus and Moritz for constantly reminding me of things in life that are way bigger than two letters in front of a name will ever be.

Abstract

As robots become increasingly affordable, they are used in ever more diverse areas in order to perform increasingly complex tasks. These tasks are typically preprogrammed by a human expert. In some cases, however, this is not feasible – either because of the inherent complexity of the task itself or due to the dynamics of the environment. The only possibility then is to let the robot learn the task by itself. This learning process usually involves a long training period in which the robot experiments with its surroundings in order to learn the desired behavior. If robots have to learn a shared goal in a group, the robots should imitate each other in order to reduce their individual learning time. The question how this can be done in a robot group has been considered in this thesis, i. e., how robots in a group can *learn* to achieve their shared goal and *imitate* each other in order to increase the performance and the speed of learning by spreading the learned knowledge in the group.

To allow for this intertwined learning and imitation, a dedicated robot architecture has been developed. On the one hand, it fosters autonomous and self-exploratory learning. On the other hand, it allows for manipulating the learned knowledge and behavior to account for new knowledge gathered by the imitation process. Learning of behavior is achieved by separately learning at two levels of abstraction. At the higher level, the strategy is learned as a mapping from abstract states to symbolic actions. At the lower level, the symbolic actions are grounded autonomously by learned low-level actions.

The approaches of imitation presented in this thesis are unique in that they relieve the requirements that governed multi-robot imitation so far. It enables robots in a robot group to imitate each other in a non-obtrusive manner. The robots can thus increase their learning speed and thereby the overall performance of the group by simply observing the other group members without requiring them to stick to a certain communication protocol that would provide the necessary information. With the presented approach, a robot is able to infer the behavior that the observed demonstrator is performing and to replay the beneficial behavior with its own capabilities.

In addition, the presented approaches allow the robots to apply imitation even if the group is heterogeneous. Normally, the performance of a group degrades if robots with incompatible capabilities imitate each other. Capability differences arise if robot morphologies differ in a robot group. This is the case if different robots from different manufacturers form a robot group that has to achieve shared goals. This thesis presents an approach that is able to determine similarities or differences between robots. This can guide the robots in a heterogeneous robot group in order to determine those robots for imitation that are most similar to themselves.

第一章 绪论	1
第一节 绪论	1
第二节 绪论	1
第三节 绪论	1
第四节 绪论	1
第五节 绪论	1
第六节 绪论	1
第七节 绪论	1
第八节 绪论	1
第九节 绪论	1
第十节 绪论	1
第十一章 绪论	1
第十二章 绪论	1
第十三章 绪论	1
第十四章 绪论	1
第十五章 绪论	1
第十六章 绪论	1
第十七章 绪论	1
第十八章 绪论	1
第十九章 绪论	1
第二十章 绪论	1
第二十一章 绪论	1
第二十二章 绪论	1
第二十三章 绪论	1
第二十四章 绪论	1
第二十五章 绪论	1
第二十六章 绪论	1
第二十七章 绪论	1
第二十八章 绪论	1
第二十九章 绪论	1
第三十章 绪论	1
第三十一章 绪论	1
第三十二章 绪论	1
第三十三章 绪论	1
第三十四章 绪论	1
第三十五章 绪论	1
第三十六章 绪论	1
第三十七章 绪论	1
第三十八章 绪论	1
第三十九章 绪论	1
第四十章 绪论	1
第四十一章 绪论	1
第四十二章 绪论	1
第四十三章 绪论	1
第四十四章 绪论	1
第四十五章 绪论	1
第四十六章 绪论	1
第四十七章 绪论	1
第四十八章 绪论	1
第四十九章 绪论	1
第五十章 绪论	1
第五十一章 绪论	1
第五十二章 绪论	1
第五十三章 绪论	1
第五十四章 绪论	1
第五十五章 绪论	1
第五十六章 绪论	1
第五十七章 绪论	1
第五十八章 绪论	1
第五十九章 绪论	1
第六十章 绪论	1
第六十一章 绪论	1
第六十二章 绪论	1
第六十三章 绪论	1
第六十四章 绪论	1
第六十五章 绪论	1
第六十六章 绪论	1
第六十七章 绪论	1
第六十八章 绪论	1
第六十九章 绪论	1
第七十章 绪论	1
第七十一章 绪论	1
第七十二章 绪论	1
第七十三章 绪论	1
第七十四章 绪论	1
第七十五章 绪论	1
第七十六章 绪论	1
第七十七章 绪论	1
第七十八章 绪论	1
第七十九章 绪论	1
第八十章 绪论	1
第八十一章 绪论	1
第八十二章 绪论	1
第八十三章 绪论	1
第八十四章 绪论	1
第八十五章 绪论	1
第八十六章 绪论	1
第八十七章 绪论	1
第八十八章 绪论	1
第八十九章 绪论	1
第九十章 绪论	1
第九十一章 绪论	1
第九十二章 绪论	1
第九十三章 绪论	1
第九十四章 绪论	1
第九十五章 绪论	1
第九十六章 绪论	1
第九十七章 绪论	1
第九十八章 绪论	1
第九十九章 绪论	1
第一百章 绪论	1

Contents

1	Introduction	1
1.1	Objectives and contributions	3
1.2	Thesis outline	4
2	State of the art	7
2.1	Learning	7
2.1.1	Supervised	7
2.1.2	Unsupervised	8
2.1.3	Reward-based	8
2.2	Imitation	8
2.2.1	Biological background	9
2.2.1.1	Categorizing imitation	9
2.2.1.2	Imitation and memetics	11
2.2.1.3	Imitation in biology	11
2.2.2	Imitation in robotics	12
2.2.2.1	Challenges in robot imitation	12
2.2.2.2	Programming by demonstration	14
2.2.2.3	Imitation in multi-robot systems	15
2.2.3	Contrasting the thesis to the state of the art approaches	15
3	Architecture for learning and imitating in groups	17
3.1	Architectural overview	18
3.1.1	Motivation layer	19
3.1.2	Strategy layer	19
3.1.3	Skill layer	20
3.2	Layer interaction	20
3.3	Imitation in robot groups	21
3.4	Choice of the imitatee	23

3.5	Scenarios	23
4	Motivation layer	25
4.1	Background	25
4.1.1	Motivation in biological autonomous systems	26
4.1.2	Use of motivation in robots	27
4.2	Design of a robotic motivation system	28
4.2.1	Excitation	30
4.2.2	Prioritizing goals	30
4.3	Conclusion	30
5	Strategy layer	33
5.1	Background	36
5.1.1	Markov decision processes	36
5.1.1.1	Policy	37
5.1.1.2	Solving Markov decision processes	38
5.1.2	Semi-Markov decision processes	39
5.2	State of the art	39
5.2.1	Model-free approaches	39
5.2.2	Model-based approaches	40
5.2.3	Discussion	41
5.3	Policy	41
5.4	State abstraction	44
5.5	Model	46
5.5.1	Transition heuristic	46
5.5.2	Failure heuristic	47
5.5.3	Reward heuristic	48
5.5.4	Simplification heuristic	49
5.5.5	Experience heuristic	49
5.6	Sample frequency	49
5.7	Exploration	50
5.8	Example	52
6	Skill layer	55
6.1	Two modes of operation	56
6.1.1	Exploration mode	56
6.1.2	Exploitation mode	57
6.1.3	Interface with the environment	57
6.2	Component description	58
6.2.1	Skill manager	61
6.2.1.1	Skill generation	62
6.2.1.2	Skill ranking	62
6.2.1.3	Skill notification	62
6.2.2	Model manager	64
6.2.2.1	Creating and updating models	64

6.2.2.2	Scoring models	65
6.2.3	Error minimizer	65
6.3	Configuration	66
6.4	Conclusion	67
7	An integrative example	69
7.1	Implementation of the motivation layer	69
7.2	Implementation of the strategy layer	70
7.3	Implementation of the skill layer	72
7.4	Evaluation	73
8	Imitation in robot groups	77
8.1	Related work	77
8.2	Overview of the multi-robot imitation approach	79
8.3	Transforming observations	81
8.4	Understanding observed behavior	83
8.4.1	Viterbi	84
8.4.2	Interpreting observed behavior	84
8.4.3	Example	88
8.5	Integrating recognized behavior	90
8.6	Evaluation	92
8.6.1	CTF with three bases	93
8.6.2	CTF with five bases	97
8.7	Conclusion	100
9	Choice of the imitatee	101
9.1	Related work	102
9.2	Background	103
9.2.1	Bayesian networks and how to learn them	103
9.2.2	Affordances	105
9.3	Overview of the demonstrator choice process	106
9.4	Affordance detection	107
9.5	Affordance network generation	108
9.6	Comparing affordance networks	112
9.6.1	Structural difference of affordance networks	112
9.6.2	Parameter difference of affordance networks	114
9.6.3	Affordance network distance metric	120
9.7	Evaluation	120
9.7.1	Experimental setup	121
9.7.1.1	Parameterization of the environment	121
9.7.1.2	Affordances and their validation	123
9.7.1.3	Imitated behavior and how to measure its success	123
9.7.2	Selection experiment	124
9.7.2.1	Scenario	124
9.7.2.2	Procedure	125

9.7.2.3	Result	125
9.7.3	Robustness experiment	128
9.7.3.1	Scenario	128
9.7.3.2	Procedure	128
9.7.3.3	Result	128
9.7.4	Clustering experiment	129
9.7.4.1	Scenario	130
9.7.4.2	Procedure	130
9.7.4.3	Results	131
9.8	Conclusion	132
10	Summary and outlook	133
10.1	Summary	134
10.2	Contributions	134
10.3	Outlook	136
A	Notation	137
B	Algorithms	139
	List of Figures	143
	List of Tables	145
	Own publications	147
	Bibliography	151

Introduction

By three methods we may learn wisdom: First, by reflection, which is noblest; Second, by imitation, which is easiest; and third by experience, which is the bitterest.

Confucius, Chinese philosopher

Of the methods by which we can gather wisdom or knowledge, *imitation* is often considered as an inferior shortcut to the more creative “noble” or “bitter” ones. The *imitator* is thereby contrasted as dumb or lazy against the creative and eager *imatee*. Yet, imitation is one of the most powerful means to spread learned knowledge. With imitation, the imitator is relieved from individual exploration, which leads to a drastic speedup of the learning process. This thesis explores approaches that allow imitation to be combined with individual learning in heterogeneous robot groups. It will be shown, how the learning speed of the robot group can be increased and thus the self-organization of the group can be supported.

As a matter of fact, imitation plays an important role in the development of humans (Fig. 1.1). They are able to imitate at an age as early as 12 days [123]. Being such a powerful means of knowledge acquisition, imitation also has been observed in animals [50]. The imitation incidents show significant differences in quality, though. There is, e. g., the more intelligent version of imitation – often found in humans – that tries to analyze and interpret the imitatee’s actions, in order to infer their original purpose. The other side of the spectrum shows a much simpler imitation type, called mimicry, which tries to copy only the actions or appearance of the imitatee. Independent of the sophistication level of imitation, it obviously pays off in nature.

For the above reasons, imitation has already been widely adopted in robotics research (cf. Chap. 2). The possibility to let robots in a group benefit from each other’s experience not only speeds up the learning phase, which is essential in today’s complex robots. It also decreases wear out and damage, which is often involved in the exploration process.



Figure 1.1: Humans are capable of imitation at an early age

When trying to provide robots with imitation capabilities, one is faced with three challenges corresponding to the three steps involved in imitation [44]:

- *Recognition*: Salient bits of the observed behavior have to be extracted from the raw observation.
- *Transformation*: The recognized complex behavior has to be transformed from the perspective of the imitator into a data structure that is comprehensible for the imitator.
- *Generation*: New behavior has to be generated from the properly encoded data.

Current research often focuses on one of these challenges, requiring everything else to be specified by hand – mostly in a context where a human is the imitator and the robot has to reproduce the observed task [28, 51, 60]. Attempts that employ imitation in a multi-robot context combining learning and imitation so far still require important challenges to be solved by the human expert beforehand, such as the actuator mapping between the imitator and the imitator or even the possibility to look into the other robot's internal data structures [142, 175].

What is still missing, is a truly autonomous multi-robot imitation approach. That is an imitation approach that does not require human intervention to solve any of the imitation-specific challenges. In this case, the following requirements have to be met:

- The imitation approach has to rely only on subjective information perceived directly by robot's sensors.
- A robot has to decide autonomously when it is imitating and when it is learning individually.
- A robot has to decide autonomously what to imitate and how to integrate the observed behavior into its own behavior knowledge.