

Richert

Learning and imitation in heterogeneous robot groups



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Herausgegeben von
Published by

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

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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

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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

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.

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