

Wilhelm Richert

Learning and imitation in heterogeneous robot groups

#### C-LAB Publication

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Richert

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#### **C-LAB Publication**

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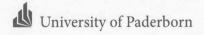
Dr. Wolfgang Kern, Siemens AG Prof. Dr. Franz-Josef Rammig, Universität Paderborn

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.

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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.



# 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.)

#### Supervisors:

Prof. Dr. Franz J. Rammig, University of Paderborn Prof. Dr. Hans Kleine Büning, University of Paderborn Prof. Dr. Uwe Brinkschulte, University of Frankfurt

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#### 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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CHAPTER ]

#### 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 *imitatee*. 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.

1



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 imitatee 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 imitatee 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 imitatee 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.