Multi Robot Learning by Demonstration

(Extended Abstract)

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ABSTRACT

In this paper, we investigate the feasibility of a Multi Robot Learning by Demonstration system, which allows multiple teachers to give a demonstration to multiple robots simultaneously. A novel, complete end-to-end system was developed, which extracts data from a live human group demonstration, and allows the robots to imitate the demonstration by adapting the demonstration dataset to the current, possibly different environment. The complete system was evaluated using a series of increasingly difficult benchmark experiments, including a collaborative door opening experiment using a group of heterogeneous robots. The results showed, that the system is resistant to changes in the environment, as it was possible to give a demonstration in one environment, move the robots to a physically different but similar location, where the robots could still imitate the demonstration in this new context. The door opening experiment also shows that this system can be used to demonstrate and learn collaborative behaviour. Our results demonstrate a novel and promising method for teaching a group of robots to perform a joint task by human team demonstration.

Categories and Subject Descriptors

I.2.9 [**Computing Methodologies**]: Artificial Intelligence—*Robotics*

General Terms

Algorithms, Experimentation

Keywords

multi-robot systems, robot, learning, learning by demonstration, adaptation, template matching, imitation

1. INTRODUCTION

The Learning by Demonstration (LbD) paradigm has been suggested as a method to tackle the complexity of robot programming. To date however, research into LbD systems has mostly focused on "a single robot being taught by a single teacher" [1]. The scenario of multiple teachers teaching multiple robots has so far received little research attention, especially regarding LbD systems in which multiple teachers teach multiple robots *simultaneously* [4]. This paper will investigate the feasibility of such a multi robot Learning by Demonstration system by developing and testing such an end-to-end system.

One challenge common to most LbD systems is the question of how to deal with an "undemonstrated state" [1]. This challenge arises because it is unlikely for a teacher to be able to demonstrate the correct behaviour for every possible state the robots may find themselves in [1], and hence it is necessary to develop a strategy for coping with new situations. Here, we shall take the approach of *adapting* the demonstration dataset to a new situation, using the (plan) adaptation algorithm presented in [5]. The plan adaptation algorithm was presented in the context of multi robot path planning, and essentially represents the environment using point features. These are recorded for the demonstration (the *template*) and the new imitation environment (the *target*). Then, the correspondences between features in the template and the target are found, and used to find a mapping that can *warp* the target to fit the new context, yielding an *adapted plan*.

In order to develop a full, end-to-end multi robot learning by demonstration system, based on the described plan adaptation approach, three components are required: a "template extraction system", which extracts the demonstration data from the environment, a "plan adaptation system", which adapts one or more templates to the new context, and a "plan execution system", which executes the adapted plan on the robots.

2. METHODOLOGY

2.1 Template extraction

The template extraction process starts with creating a laser-scan based map of the local demonstration context. Next, this map is converted to "corner" and "wall" point features, using Harris corner detectors [3], and a sliding window algorithm, respectively. The latter classifies a static obstacle as a wall feature if no other wall feature has been found within the current window.

During the demonstration, the robot location on the map is tracked using AMCL [2], and the features close to the robots are identified (marked) using a K-Nearest Neighbour (KNN) search. More specifically, the feature closest to the robot that has *not yet been marked* will be marked. Next, about half of the selected "wall" features will be deselected to avoid over-constraining the template, which is done us-

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ing another KNN search based algorithm: this one essentially tries to "hop" from one marked wall feature to the next, deselecting every other one. The remaining marked features will be "required to match", (F_r, as defined in [5]), and the marked corner features will additionally be required to match to exactly one feature in the target (F_{11} in [5]). This data gives us the template.

2.2 Plan adaptation & execution

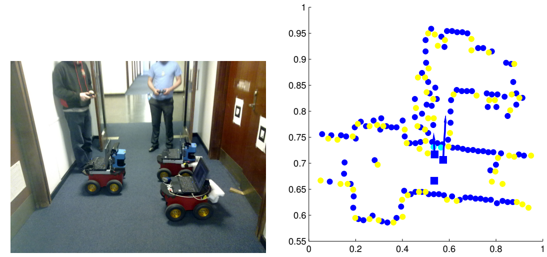
The plan adaptation system extracts a representation of the environment and the robots' relative location using the same techniques as described in section 2.1. These are sent to the plan adaptation algorithm of [5], which has been extended to take the waypoint order into account when mapping the robots in the template to the ones in the target. The resulting adapted waypoints are then sent to the robots.

The last part consists of sending the adapted waypoints to the robots, taking into account the (adapted) waypoint order. We used the ROS navigation stack to drive to robots to waypoints.

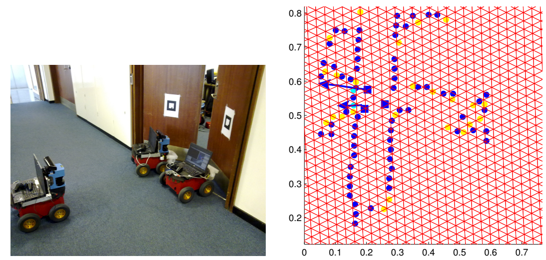
3. RESULTS & DISCUSSION

In order to evaluate the end-to-end system, a series of increasingly difficult benchmark experiments were designed. These started with two humans demonstrating to two robots how to drive straight ahead along a corridor, and then requesting an imitation in the same context. Next, the various parameters of the experiments were varied: a) the number of robots was increased to three, b) the demonstrated movements were varied (e.g. curved trajectories around a corner, intersecting trajectories), c) the demonstration and imitation environments were changed, such that the robots were given a demonstration in one context and asked to imitate in another, and d) the robots' relative displacement (their formation) was varied. It was also verified, that the template could be mirrored, scaled, translated and rotated to match a target. Furthermore, a collaborative door opening experiment was performed to see whether this type of system could be used to demonstrate collaborative behaviour to a group of robots (see Figure 1).

From these experiments, it was observed that the system was resilient to changes in the context (environment): the robots could be demonstrated how to open a door in one location, and then perform the imitation at another, similar door in a different environment. The algorithms were also tolerant to about 30-60cm of displacement of each robot from their original position in the robots' formation (in a 2m wide corridor). We verified this by taking a template and a matching target from our experiments, and applying a simulated, spiral-shaped displacement to one robot at a time, and running the matching algorithm on the changed target. This tolerance will vary depending on the template and target though, and further work is required to quantify this for a larger sample of scenarios.



(a) Template obtained from demonstration



(b) Autonomous execution of adapted plan

Figure 1: The results of the collaborative door opening experiment. Two robots are equipped with bumpers, while the one at the back uses the Microsoft XBox Kinect camera to detect the markers (cyan dots). Blue dots represent "wall features", while yellow dots represent corners.

4. CONCLUSION

This work presented one approach to developing an end-to-end Multi Robot Learning by Demonstration system, that allows multiple teachers to give a demonstration simultaneously to multiple robots, thus allowing the demonstration of collaborative behaviour. The experiments consisted of both a series of tests used to gain insights into the system's performance in various scenarios, as well as an experiment in which a group of robots was demonstrated how to collaboratively open a marked door. The experiments showed, that the system coped well with changes in the environment, and that it allowed for small displacements of the robots relative to each other. In conclusion, this paper showed the feasibility of a Multi Robot Learning by Demonstration system and will hopefully lead to further work in that area, ideally leading to users being able to customise the behaviour of groups of robots in the field.

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