Learning the Relation of Motion Control and Gestures Through Self-Exploration

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***Abstract*—This work presents an action execution system that uses as foundation very basic sensorimotor schemes. These schemes are learned as a product of the interaction with an agent with its environment. In the example experiment, a mobile agent learns an association between changes in its sensory perception and the movements it performs. Once it has this acquired knowledge, the agent is then capable of performing a mirror action to match an observed gesture. This is seen as a first step toward learning motor control strategies for a robot control task.**

I. Introduction

Human-robot interaction is usually confined within the research laboratories. As a step of moving robots outside of laboratories and into the real world, a robot waiter scenario is proposed, which is based on integration of multiple research areas into a final platform [8]. Toward this goal, robot control based on gesture recognition was considered [3, 5]. This paper presents the recognition and execution of direction gestures, namely left, right, up and down, as a mean for basic robot control and attention manipulation. The motor control strategy is a result of learning internal models through sensorimotor exploration, as demonstrated by Dearden and Demiris [4]. Changes in sensory input, represented by the changes of the location of the person's right hand, are observed during learning solely as a result of the robot's exploration.

The goal of the presented experiment is to display the viability of learning motor control based on self-exploration. The presented approach could also be applied to other scenarios, such as learning tool-use [11], learning how to focus eyes on a particular object, learning relations between a motor command and position of the end effector in space – in general the result of particular motor actions on the robot's environment. A relation between a motor command and its consequence would be learned from the collected data. This relation can be also used in the other direction – if the robot has a particular goal or state that needs to be reached, the relation could predict what is the appropriate motor command that would take the robot to the desired state.

The topic of learning inverse kinematics has been an area of interest for some time. D'Souza et al. presented a method for learning inverse kinematics for a robot arm using locally weighted projection regression [6]. A similar approach is presented by Lapreste et al. [9]. However, the approach presented here does not employ machine optimization strategies, yet achieves sufficient results for the rotation task. Previous work by Schillaci et al. showed that a similar approach can be used to learn a motor control strategy for pointing or reaching for a robot arm using motor babbling during learning and internal models for prediction [11]. An argument for importance of internal models in motor learning and possible approaches is given by Wolpert et al. [15].

II. Internal Models and Gesture Recognition

A. Internal Models

Internal models represent a theoretical concept, consisting of a pair of inverse and forward models, represented in figure 1. Depending on a problem, an inverse model can predict a motor command M_t that leads the system from the current state S_t to a desired state S_{t+1}, or, based on the observed change of states from S_t to S_{t+1}, predicts an appropriate motor command M_t. The forward model performs an internal simulation and predicts the state S^*_{t+1} that would be the result of the motor command M_t in the state S_t.

Similar to our approach, Dearden and Demiris perform learning of forward models for action execution [4]. In their work, a mobile robot observes the motion of its gripper while sending to it random motor commands. A forward model is obtained, that establishes the connection between motor commands and the changes in the visual space caused by those motor commands. This way, the system is able to imitate human movements.

Akgün et al. [1] show how an action generation mechanism can be used for action recognition. They developed an online recognition system, that was able to recognize a reaching action before it was fully executed.

Haruno et al. [7] and Wolpert and Kawato [16] present evidence for development of multiple, tightly-coupled inverse and forward models. The forward model predicts the result of the motor command generated by the inverse model. The selection of the best inverse-forward model pair is done through comparison of predictions of all forward models to the expected result. Schillaci et al. [12] used multiple internal models to perform recognition of human behavior, where each internal model encodes an action. Blakemore et al. [2] present how a difference in the prediction of the forward model and the perceived sensory input helps a person discriminate a self-induced sensation (e.g. self-movement of the eye) from a sensation induced by others (e.g. moving the eye by pressing on the eyelid). Furthermore, Takemura and Inui [14] present a model for the development of internal models for reaching movement, inspired by infant development.

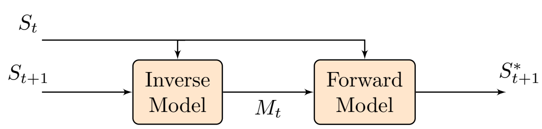

Fig. 1. Internal models. An inverse model predicts a motor command M_t that leads the system from the current state S_t to S_{t+1}. A forward model predicts the state S^*_{t+1} based on the current state S_t and the motor command M_t.

B. Gestures

As presented in [13], certain aspects of robot behavior have been identified in order to increase intuitiveness of interaction, such as enhanced feedback from the robot. Robot pointing was used to manipulate human attention. On the other side, gestures can be used to manipulate robot attention and to indicate intentions of a human participant. Therefore, robust gesture recognition is important for a satisfying, real-life human-robot interaction.

Gesture recognition is based on detection of the position (static) or the motion (dynamic) of human body parts, usually arms, hands and legs. It has numerous applications, including sign-language for hearing-impaired people, computer interfaces, natural and intuitive human-robot interaction, gaming industry, system remote control, among others. Various tools have been used for gesture recognition, based on the approaches ranging from statistical modeling, computer vision and pattern recognition, image processing, connectionist systems, etc. [10].

However, learning from self-exploration to observe and reproduce certain actions from gestures of others has not been done before, apart from work of Dearden and Demiris [4]. The proposed model learns to execute actions associated with directional gestures. The learned motor controls are a result of a motor babbling process, during which a random motor command is generated and a change in the sensory input is observed and stored.

III. Proposed Model

The proposed model uses as sensory situation the detected coordinates of the arm of a person as tracked by a Kinect. The motor commands are fixed movements of the mobile platform.

In our model, we want to perform the fusion of sensorimotor information. To achieve this, the system needs to collect, for each time step, a vector of the form:

$$(x, y, z); M \qquad (1)$$

where (x, y, z) represent the coordinates of the hand detected by the Kinect and M represents a random motor movement. This movement can be either in the left-right plane, performed by the robot as a rotation for a random angle, within $[-27°, 27°]$ or in the up-down plane, performed as a tilt angle in the Kinect within $[0°, 16°]$ (ranges were selected to always have the person's upper body visible).

Once a database of these associations is collected, it can be used as either a forward or an inverse model, depending on the question asked.

The inverse model predicts a motor command M_t, when presented with a change in the sensory situation from S_t to S_{t+1}. The forward model, given the current sensory situation S_t and a motor command M_t predicts the new sensory situation after the execution of the command, S^*_{t+1}. In the proposed application, that is a gesture-controlled robot, during the learning process random motor commands induce changes in sensory situations, that is in the position of the hand. The model associates the performed motor command M_t with the sensory situation before the execution S_t and after the execution S_{t+1}. During execution the model performs a search for a motor command M_t that matches the sensory change, only this time induced by a person by moving their hand.

It could be said, that the model learns how to execute actions. It learns how the self-motion corresponds to changes in the world, which is then applied during the execution, when it is required to reproduce an action that resulted in the observed change. The resulting behaviour can be also seen as an attention manipulation system, where the robot turns following the motion of a hand.

IV. Experiments and Results

Two experiments were performed to learn the mapping between the motor commands and changes in the sensory situation. A robot platform robuLAB, displayed in figure 2, was used in the experiments. In the first experiment, the association of "up" and "down" gestures and Kinect's up and down movements was formed, while in the second experiment the association of "left" and "right" gestures and the rotation of the robuLAB platform was learned. The following description shows the outline of both experiments, and "the platform" represents either the Kinect or the robot platform. In the former case, the motor commands were tilting the Kinect, while in the latter they were rotation of the robot platform around the z-axis.

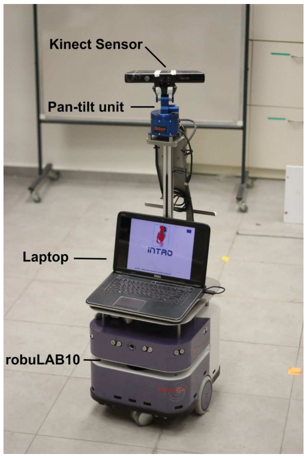

Fig. 2. Experimental platform

A person stood in front of the platform at the beginning of the experiment. The Kinect was tracking the location of the person's right hand, provided by the Microsoft's Kinect SDK. During the learning stage the platform was performing motor babbling, which was a generation of random motor commands. Every motor command induced a change in the sensory situation, that is the change of the 3D location of the person's hand. This change, represented with the (x, y, z) vector of the hand movement in Kinect's frame of reference, corresponds to the rotation angle of the platform. In other words, if the platform rotates to the left, the hand will be seen as moving right. However, during the execution phase, if the platform perceives the hand moving right, it should rotate to the right, instead of left. During the learning process, initial rotation of the platform and the generated random motor command, represented as a rotation angle, was stored, as well as the 3D position of the hand before and after the rotation.

A k-nearest neighbors search algorithm was used for implementation of the inverse model. Theoretically, the initial state S_t represents the initial position of the hand, and the next state S_{t+1} the new position of the hand, resulting from the person's movement. The predicted motor command M_t represents the rotation angle of the robot that it needs to perform in order to compensate for the motion of the person's hand. However, in order to make the implementation more robust with regards to the person's location in space, S_t and S_{t+1} are combined and represented as the difference vector of the new and the initial location of the person's hand.

When the platform observes the movement of the person's arm, it uses the perceived change in the hand's location to predict a motor command that will compensate for the motion of the arm. The resulting action can be seen as recognition of a dynamic gesture and its corresponding motion.

Testing of the algorithm was done using the rotation of the robuLAB platform. Training was performed with 60 points from motor babbling. Testing was performed with hand movements to the left or to the right for 25 times. On average, absolute hand displacement of the user was $(x, y, z) = (0.43, 0.24, 0.06)m, s.d. = (0.13, 0.12, 0.05)$ and the error of the prediction resulted in the absolute mismatch between the initial hand position and the hand position after the rotation of $(x, y, z) = (0.08, 0.24, 0.06)m, s.d. = (0.06, 0.12, 0.04)$. The results show that this approach can be used for learning motor control for rotation based on the depth data of the user's hand.

V. Conclusion and Future Work

This work presents learning and execution of an inverse-forward model pair to execute actions associated with directional gestures. While only the inverse model was trained, the forward model could be easily added and used to predict the hand location after the robot's movement. This information can be used for error measurement of the prediction and refinement of the initial motion, if the error is higher then a certain threshold. Future work could improve the proposed model to understand pointing gestures, with the goal of learning a control strategy for moving to a specific location. This location would be indicated by a person pointing.

Acknowledgments

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