ROBOT SKILL SYNTHESIS THROUGH HUMAN VISUO-MOTOR LEARNING

Humanoid Robot Statically-stable Reaching and In-place Stepping

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Abstract: To achieve a desirable motion of the humanoid robots we propose a framework for robot skill-synthesis that is based on human visuo-motor learning capacity. The basic idea is to consider the humanoid robot as a tool that is intuitively controlled by a human demonstrator. Once the effortless control of the humanoid robot has been achieved, the desired behavior of the humanoid robot is obtained through practice. The successful execution of the desired motion by the human demonstrator is afterwards used for the design of motion controllers that operate autonomously. In the paper we describe our idea by presenting a couple of robot skills obtained by the proposed framework.

1 INTRODUCTION

If robots could be able to imitate human motion demonstrated to them, acquiring complex robot motions and skills would become very straightforward. One can capture the desired motion of a human subject and map this motion to the kinematical structure of the robot. Due to the different dynamical properties of the humanoid robot and the human demonstrator, the success of this approach with regard to the stability of the humanoid robot depends on the ad-hoc mapping implemented by the researcher (Schaal, 1999). Here we propose a very different approach where we use the human demonstrators real-time action to control the humanoid robot and to consecutively build an appropriate mapping between the human and the humanoid robot. This effectively creates a closed loop system where the human subject actively controls the humanoid robot motion in real time with the requirement that the robot stays stable. This requirement can be easily satisfied by the human subject because of the human brain ability to control novel tools (Oztop et al., 2006; Goldenberg and Hagmann, 1998). The robot that is controlled by the demonstrator can be considered as a tool such as a car or a snowboard when one uses it for the first time. This setup requires the humanoid robots state to be transferred to the human as the feedback information.

The proposed closed-loop approach exploits the human capability of learning to use novel tools in order to obtain a motor controller for complex motor tasks. The construction of the motor controller has two phases. In the first phase a human demonstrator performs the desired task on the humanoid robot via an intuitive interface. Subsequently in the second phase the obtained motions are acquired through machine learning to yield an independent motor controller. The two phases are shown on Figure 1.

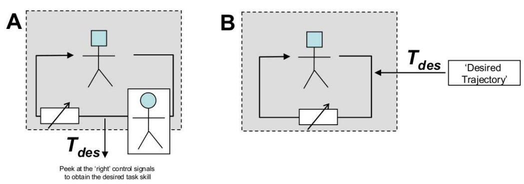

Figure 1: (A) Human demonstrator controls the robot in closed loop and produces the desired trajectories for the target task. (B) These signals are used to synthesize a controller for the robot to perform this task autonomously.

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In the following sections, we present two example skills that were obtained by the described framework.

2 STATICALLY STABLE REACHING

The proposed approach can be considered as a closed loop approach where the human demonstrator is actively included in the main control loop as shown on Figure 2. The motion of the human demonstrator was acquired by the contact-less motion capture system. The joint angles of the demonstrator were fed forward to the humanoid robot in real-time. In effect, the human acted as an adaptive component of the control system. During such control, a partial state of the robot needs to be fed back to the human subject. For statically balanced reaching skill, the feedback we used was the rendering of the position of the robot's centre of mass superimposed on the support polygon of the robot which was presented to the demonstrator by means of a graphical display. During the experiment the demonstrator did not see the humanoid robot.

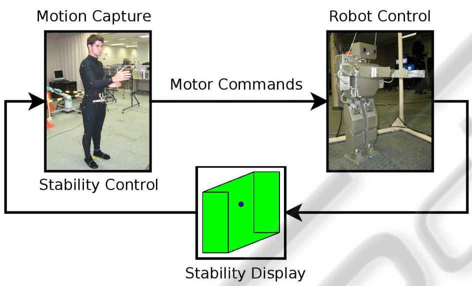

Figure 2: Closed-loop control of the humanoid robot. Motion of the human is transfered to the robot while the robot's stability is presented to the human by a visual feedback.

The demonstrator's task was to keep the center of mass of the humanoid robot within the support polygon while performing the reaching movements as directed by the experimenter. With a short practice session the demonstrator was able to move his body and limbs with the constraint that the robot's center of mass was within the support polygon. Hence the robot was statically stable when the demonstrator generated motions were either imitated by the robot in real-time or played back later on the robot. The robot used in the study was Fujitsu HOAP-II small humanoid robot.

The motion of the humanoid robot was constrained to the two dimensions; only the vertical axis and the axis normal to the trunk were considered. The light wiggly curve on Figure 3 shows the robot end-effector position data which was generated by the demonstrator. One can imagine the humanoid robot from its left side standing with the tips of the feet at the centre of the coordinate frame and reaching out outwards with its right hand gliding over the curve. The long straight segment of the curve connects the beginning and the end of the reaching motion.

For each data point of the obtained end-effector trajectory, the robot joint angles were recorded. Assuming rows of the humanoid robot end-effector position $\mathbf{X}$ is formed by the data points taken from the obtained end-effector trajectory and the robot joint angles $\mathbf{Q}$ is formed by the corresponding joint angles we get a non-linear relation of the form

$$\mathbf{Q} = \Gamma(\mathbf{X})\,\mathbf{W}. \tag{1}$$

By performing a non-linear data fit and solving for $\mathbf{W}$ we can afterwards make prediction with

$$\boldsymbol{q}_{pred} = \Gamma(\boldsymbol{x}_{des})\,\mathbf{W} \tag{2}$$

where $\boldsymbol{q}_{pred}$ is a vector of the predicted joint angles and $\boldsymbol{x}_{des}$ is a vector of the desired end-effector position. Using the prediction we can afterwards ask the humanoid robot to reach out for a desired position without falling over.

For non-linear data fitting the recorded positions $\mathbf{X}$ are mapped into an N dimensional space using the Gaussian basis functions given by

$$\varphi_i(\boldsymbol{x}) = e^{\frac{\boldsymbol{x}-\mu_i}{\sigma^2}} \tag{3}$$

where μ_i and σ^2 are open parameters to be determined. Each row of $\mathbf{X}$ in converted into an N dimensional vector forming a data matrix

$$\mathbf{Z} = \Gamma(\mathbf{X}) = \begin{bmatrix} \varphi_1(\boldsymbol{x}_1) & \varphi_2(\boldsymbol{x}_1) & \dots & \varphi_N(\boldsymbol{x}_1) \\ \varphi_1(\boldsymbol{x}_2) & \varphi_2(\boldsymbol{x}_2) & \dots & \varphi_N(\boldsymbol{x}_2) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_1(\boldsymbol{x}_m) & \varphi_2(\boldsymbol{x}_m) & \dots & \varphi_N(\boldsymbol{x}_m) \end{bmatrix}. \tag{4}$$

Assuming we have a linear relation between the rows of $\mathbf{Z}$ and $\mathbf{Q}$, we can solve Eq. (2) for $\mathbf{W}$ in the sense of the minimum least squares by

$$\mathbf{W} = \mathbf{Z}^{+}\,\mathbf{Q} \tag{5}$$

where $\mathbf{X}^{+}$ represents the pseudo-inverse of $\mathbf{X}$. The residual error is given by

$$tr\left((\mathbf{XW}-\mathbf{Q})\,(\mathbf{XW}-\mathbf{Q})^{T}\right). \tag{6}$$

In effect, this establishes a non-linear data fit; given a desired end-effector position $\boldsymbol{x}$, the joint angles that would achieve this position are given by

$$\boldsymbol{q}_{pred} = \begin{pmatrix} \varphi_1(\boldsymbol{x}_{des}) & \varphi_2(\boldsymbol{x}_{des}) & \dots & \varphi_N(\boldsymbol{x}_{des}) \end{pmatrix}\mathbf{W}. \tag{7}$$

The open parameters are N as the number of basis functions which implicitly determines μ_i and the variance σ^2. They were determined using cross-validation. We prepared a Cartesian desired trajectory that was not a part of the recording data set and converted it into a joint trajectory with the current set values of (N, σ^2). The joint trajectory was simulated on a kinematical model of the humanoid robot producing an end-effector trajectory. The deviation of the resultant trajectory from the desired trajectory was used as a measure to choose the values of the open parameters.

Figure 3 shows the desired end-effector trajectory and the generated end-effector trajectory obtained by playing back the predicted joint angle trajectories on the humanoid robot. The light wiggly curve on Figure 3 represents the end-effector trajectory that was generated by the human demonstrator in the first phase and subsequently used to determine the mapping **W** between the joint angles and the end-effector position.

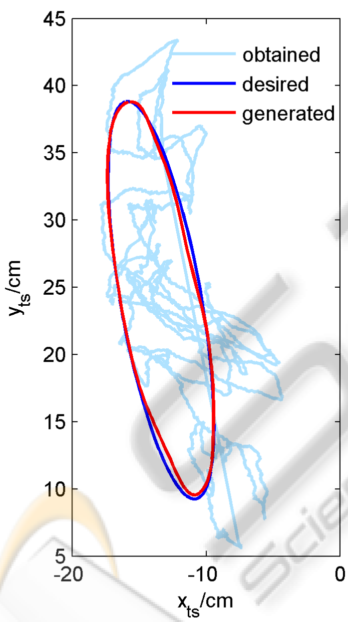

Figure 3: The obtained end-effector trajectory generated by the demonstrator (light wiggly curve) with the desired end-effector trajectory that was used as the input for the joint angle prediction and the generated end-effector trajectory obtained by playing back the predicted joint angle trajectories on the humanoid robot.

The reaching skill of the humanoid robot we obtained was statically stable which means that the robot's centre of mass was inside the robot's support polygon. A sequence of video frames representing the statically stable autonomous trajectory tracking obtained with our method is shown on Figure 4.

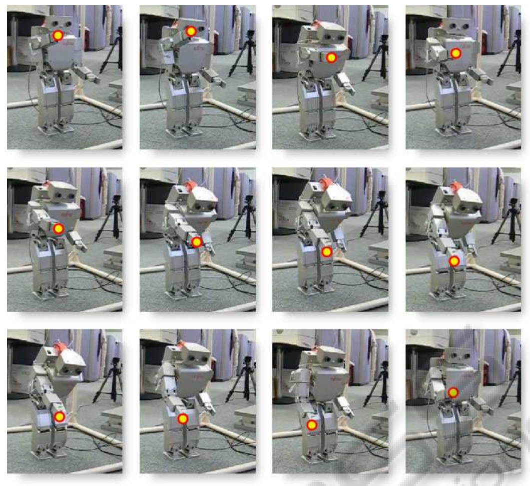

Figure 4: Video frames representing the statically stable reaching motion of the humanoid robot obtained with the proposed approach.

3 IN-PLACE STEPPING

In this section, we present our preliminary work on performing a statically stable in-place stepping of the humanoid robot. In-place stepping is a task that requires an even stricter balance control than the reaching experiment described in the previous section. In order for the humanoid robot to lift one of its feet during the statically stable in-place stepping, the robot's centre of mass needs to be shifted to the opposite leg before the lifting action occurs. As the robot's centre of mass is relatively high and the foot is relatively small, it is crucial that the position of the centre of mass of the robot can be precisely controlled. For humans, to maintain the postural stability is a very intuitive task. If one perturbs the posture of a human, he/she can easily and without any concious effort move the body to counteract the posture perturbations and to stay in a balanced posture. The main principle of our approach is to use this natural capability of humans to maintain the postural stability of the humanoid robots. In order to do so, we designed and manufactured an inclining parallel platform on which a human demonstrator is standing during the closed-loop motion transfer (Figure 5).

Instead of using visual information for the robot's stability as previously explained in the reaching experiment, the state of the humanoid robot's postural stability is feed-back to the human demonstrator by the inclining parallel platform. When the humanoid robot is statically stable, the platform stays in a horizontal position. On the contrary, when the centre of mass of the robot leaves its support polygon and therefore becomes statically unstable, the platform moves in a way that puts the human demonstrator standing on the platform in an unstable state that is directly comparable to the instability of the humanoid robot. The human demonstrator is forced to correct his/her

Figure 5: Inclining parallel platform that can rotate around all three axes. The diameter of the platform is $0.7m$ and is able to carry an adult human.

balance by moving the body. Consecutively, as the motion of the human demonstrator is fed-forward to the humanoid robot in real-time, the humanoid robot gets back to the stable posture together with the demonstrator. Using some practice, human demonstrators easily learned how to perform in-place stepping on the humanoid robot. The obtained trajectories can afterwards be used to autonomously control the in-place stepping of the humanoid robot. Our future plans are to extend this approach and use it for acquiring walking of the humanoid robots. Figure 6 shows the human demonstrator and Fujitsu Hoap-3 humanoid robot during the in-place stepping experiment.

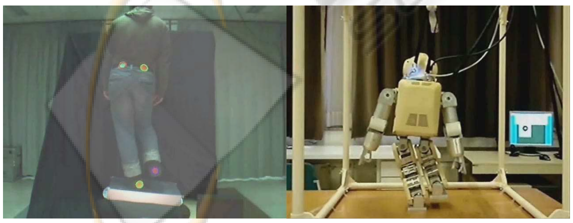

Figure 6: The human demonstrator and Fujitsu Hoap-3 humanoid robot are shown during the in-place stepping experiment. The video frame on the left side shows the human demonstrator performing in-place stepping on the inclining parallel platform. The right side frame shows the humanoid robot during the one foot posture.

4 CONCLUSIONS

A goal of imitation of motion from demonstration is to remove the burden of robot programming from the experts by letting non-experts to teach robots. The most basic method to transfer a certain motion from a demonstrator to a robot would be to directly copy the motor commands of the demonstrator to the robot (Atkeson et al., 2000) and to modify the motor commands accordingly to the robot using a sort of a local controller. Our approach is different in the sense that the correct motor commands for the robot are produced by the human demonstrator. For this convenience, the price one has to pay is the necessity of training to control the robot to achieve the desired action. Basically, instead of expert robot programming our method relies on human visuo-motor learning ability to produce the appropriate motor commands on the robot, which can be played back later or used to obtain controllers through machine learning methods as in our case of reaching.

The main result of our study is the establishment of the methods to synthesize the robot motion using human visuo-motor learning. To demonstrate the effectiveness of the proposed approach, statically stable reaching and in-place stepping was implemented on a humanoid robot using the introduced paradigm.

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