Upper-body Kinesthetic Teaching of a Free-standing Humanoid Robot

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***Abstract*— We present an integrated approach allowing a free-standing humanoid robot to acquire new motor skills by kinesthetic teaching. The proposed method controls simultaneously the upper and lower body of the robot with different control strategies. Imitation learning is used for training the upper body of the humanoid robot via kinesthetic teaching, while at the same time Reaction Null Space method is used for keeping the balance of the robot. During demonstration, a force/torque sensor is used to record the exerted forces, and during reproduction, we use a hybrid position/force controller to apply the learned trajectories in terms of positions and forces to the end effector. The proposed method is tested on a 25-DOF Fujitsu HOAP-2 humanoid robot with a surface cleaning task.**

I. INTRODUCTION

Controlling a full-body humanoid robot is an extremely difficult task, especially if the robot is standing free on its own two legs. Physical human-robot interaction with full-body humanoids has been studied in the context of assisted walking [1], helping a robot to stand up [2], or compliant human-robot interaction with a standing robot [3].

Recent advances in robotics and mechatronics have allowed for the creation of light-weight research-oriented humanoid robots, such as RobotCub's iCub, Kawada's HRP-2, Honda's ASIMO and Fujitsu's HOAP-2 (shown in Fig. 1). From a hardware point of view, these research platforms have the potential for great movement abilities: they have many DOF (degrees of freedom), permit low-level actuator control for both position and torque, and have a number of useful onboard sensors. From a software point of view, however, it is difficult to pre-program sophisticated full-body motion controllers for the huge variety of complex tasks they will face in dynamic environments.

Developing the full potential of these robots is only possible by giving them the ability to learn new tasks by themselves or by imitation of human demonstrations of tasks [4]–[6]. Such approaches give robots the ability to learn, generalize, adapt and reproduce a task with dynamically changing constraints based on human demonstrations of the task.

Traditional ways of demonstrating skills to robots require the use of vision, immersive teleoperation, or motion capture [7]. The difficulty with them is that the correspondence problem [8] needs to be addressed. Also, the lack of feedback from the robot during the demonstrations means that the teacher does not know for sure if the robot will be able to perform the skill without self-collisions or singular configurations.

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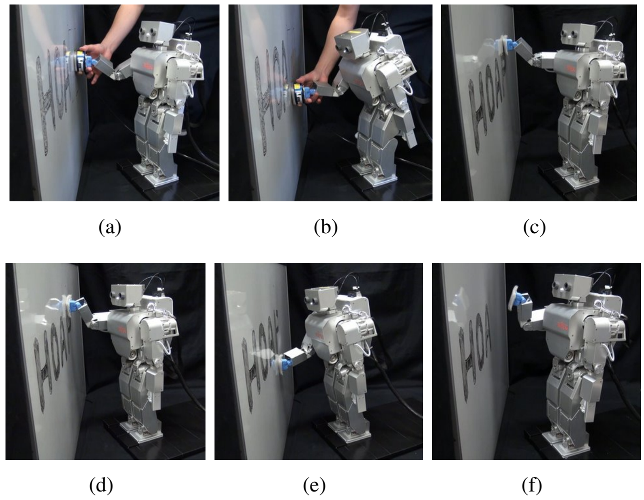


Fig. 1. Upper-body kinesthetic teaching of a free-standing HOAP-2 robot for a whiteboard cleaning task. During the teaching, the robot keeps its balance while at the same time allowing the human to move its arm. (a) The human teacher demonstrates the task by holding the hand of the robot. A simple active compliance controller is used for the arm, and reactive balance controller for the rest of the body; (b) The hip-strategy balance controller allows the robot to increase the size of the working space without falling; (c) At the beginning of the standalone reproduction, the robot extends its arm and touches the surface; (d) During task reproduction, the robot leans forward and uses the ankle torque controller and its own gravitational force to exert the required force on the surface; (e) When the reference force is bigger, the robot achieves it by leaning forward more and holding the hand closer to the body; (f) At the end of the reproduction, the robot pushes itself away from the board and returns to upright position.

An alternative modality for performing the human demonstrations is through kinesthetic teaching [9], in which the human teacher moves directly the robot's arms. Applying kinesthetic teaching to a full-body humanoid robot, however, is not trivial, because of the difficulty in performing demonstrations on many DOF simultaneously, as well as the difficulty of keeping the robot's balance during the demonstration. Due to this, previous kinesthetic teaching approaches mostly considered humanoid robots permanently attached to a supporting base, thus avoiding the problem of self-balancing (as in [9]), or by using very small servo-controlled humanoid whose body was entirely supported by the demonstrator (as in [10]). In most cases, only a small fraction of the robot's DOF are actually used (e.g. by disabling or freezing lower body motors during the teaching process). Only few works have considered imitation learning in full-body humanoid self-balancing robots [11]–[14], but not in the context of kinesthetic teaching.

The novelty of this paper is in extending the kinesthetic teaching approach to a full-body free-standing[1] humanoid robot that allows upper-body kinesthetic teaching and simultaneously keeps the robot's own balance. We propose to treat the teaching interaction as an external disturbance to the robot. We thus assume that the human demonstrator is acting as a continuous and variable external force on the upper body of the humanoid robot, which needs to be compensated by an appropriate balance controller.

A study of the dynamics and balance of a humanoid robot during manipulation tasks can be found in [15]. In [16], Hwang et al. studied the static relationship between the hand reaction force and the Zero Moment Point (ZMP) position. Harada et al. [17] did research on a humanoid robot adaptively changing the gait pattern according to the hand reaction force. A methodology for the analysis and control of internal forces and center of mass behavior produced during multi-contact interactions between humanoid robots and the environment is proposed in [18].

One promising method for balance control of a humanoid robot is based on the Reaction Null Space concept [19], [20]. The concept was originally developed for free-flying and flexible-base manipulators, but it has recently been successfully applied to humanoid robots for controlling the balance via the reactions imposed on the feet. The ankle and hip strategies for balance recovery of a biped robot based on the Reaction Null Space concept provide swift reaction patterns resembling those of humans.

In this paper we develop an integrated approach for upper-body kinesthetic teaching allowing a free-standing humanoid robot to acquire new motor skills including force interactions with external objects. In our approach, the robot is free-standing and self-balancing during both the teaching and the reproduction. We control simultaneously the upper and lower body of the robot with different control strategies allowing it to be compliant during teaching and stiff enough to exert forces during reproduction.

The proposed method is tested on a 25-DOF Fujitsu HOAP-2 humanoid robot by teaching it a surface cleaning skill. The robot is equipped with a force/torque sensor mounted on a passive two-DOF attachment at the end-effector. After being instructed how to move the arm and what force to apply with the hand on the surface, the robot learns to generalize and reproduce the task by itself. The surface cleaning task is challenging because it requires the use of a tool (e.g. sponge) to affect an external object (e.g. board), and involves both position and force information [21]. The task is a good testbed for the proposed approach because: (1) it can be taught via kinesthetic teaching; (2) it requires full-body control, especially balance control during both teaching and reproduction; (3) it requires exerting varying forces to external objects; (4) it involves integration of motor control and learning parts in one coherent task.

[1]By free-standing humanoid robot we mean self-balancing robot which is standing on its own two feet without any additional support.

II. PROPOSED APPROACH

The proposed approach consists of three consecutive phases: demonstration phase, learning phase, and reproduction phase. Fig. 2 shows a high-level outline of the approach.

A. Demonstration phase

During the demonstration phase, we use active compliance controller for the upper body (the arms including the shoulders), and a balance controller for the lower body (the legs including the hip). The experimental setup for the demonstration phase is shown in Fig. 1.

1) Active compliance controller for the upper body: Moving HOAP-2's limbs manually is possible by switching off the motors, but requires effort that limits the use of kinesthetic teaching to setups in which the robot is in a fixed seated position [22]. Because of this, it is practically impossible to do kinesthetic teaching of a free-standing HOAP-2 by simply switching off the motors of the arms, because the demonstrator's exerted forces are rapidly transmitted to the torso and the robot is prone to fall down. In order to solve this problem, we use a simple active compliance controller based on torque control mode for friction compensation with velocity feedback. We use velocity feedback, instead of torque feedback, because the HOAP-2 does not have torque sensing capabilities, but only motor current control. We use imperfect friction model, taking into consideration only the viscous friction, i.e. we consider the joint friction to be proportional to the angular velocity. Also, we use lower gains than the ones set by the manufacturer. Since the static (Coulomb) friction of HOAP-2 is very high, and the weight of the arm is light, we do not use gravity compensation. The arm of the robot keeps its current configuration if it is not touched by the user, due to the high static friction. The implemented viscous friction compensation controller helps in smooth movements, but impedes sudden sharp changes in the direction of movement. For the tasks considered by this paper this behavior is a good compromise, which aids the kinesthetic teaching significantly by making the arm move easily under the demonstrator's guidance.

2) Balance controller for the lower body: The balance controller employs two different balance strategies: ankle strategy and hip strategy [19]. According to the ankle strategy, the robot reacts in a compliant way in response to the external disturbance by displacing its CoM (center of mass). After the disappearance of the disturbance, the initial posture will be recovered. On the other hand, the essence of the hip strategy is to ensure compliant reaction to the external disturbance by bending the hips, trying thereby to displace the CoM as little as possible. This strategy has been realized with the help of the Reaction Null Space method [20]. Further on, smooth transition between the two strategies is also ensured by making use of the transition strategy recently presented in [23]. The resulting behavior is such that the balance is first controlled with the help of the ankle strategy in response to a relatively small force exerted by the human teacher. When the teacher exerts an additional force by strongly pulling the arm, e.g. to extend

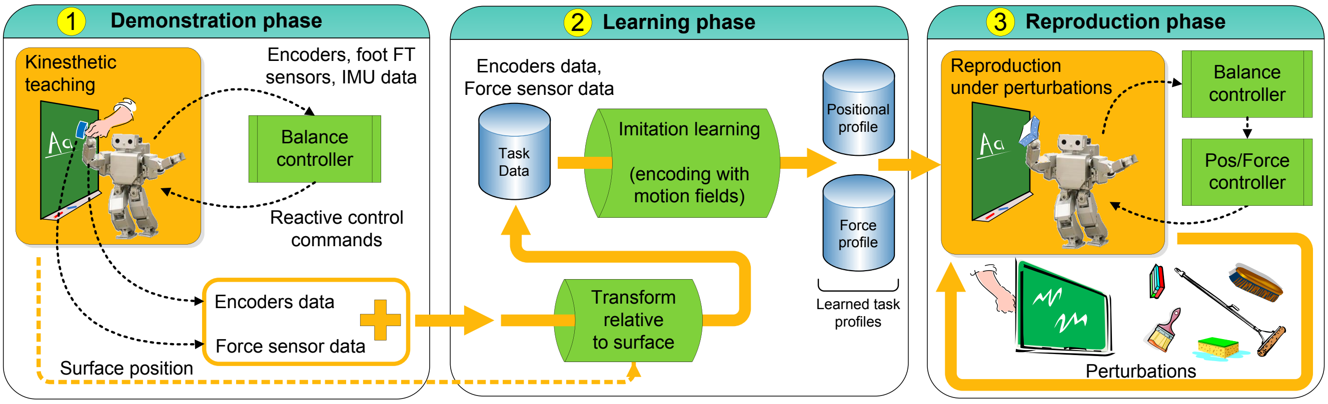


Fig. 2. Flowchart of the proposed approach, showing details about each of the three phases: demonstration, learning, and reproduction.

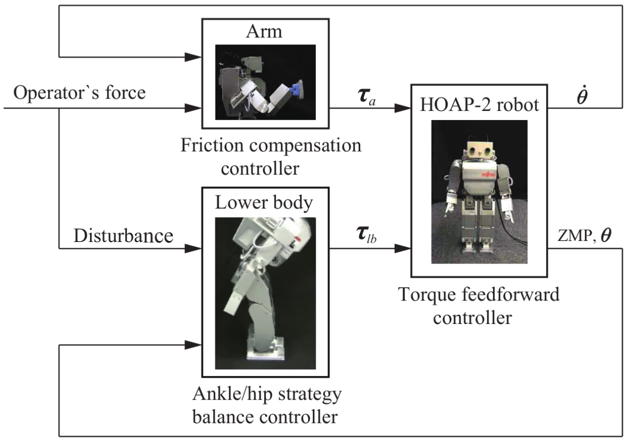


Fig. 3. Block schema of the controller used during the demonstration phase.

the reach, the robot switches smoothly to the hip strategy and bends the hips. When the strong pull is removed, the robot switches back to the ankle balance strategy. A block schema of the proposed controller used during the demonstration phase is shown in Fig. 3. The controller consists of three parts: the active compliance controller based on viscous friction compensation for the arm with velocity feedback, the balance controller with position and ZMP feedback, and a local feedforward torque controller at the joint level[2].

B. Learning phase

During this phase the recorded demonstrations are used to learn a compact representation of the skill. We propose to encode the skill based on a superposition of basis motion fields to provide a compact and flexible representation of a movement. The approach is an extension of Dynamic Movement Primitives (DMP) [24], [25] which encapsulates variation and correlation information across multivariate data. In the proposed method, a set of virtual attractors is used to reach a target. The influence of these virtual attractors is smoothly switched along the movement on a time basis. The set of attractors is learned by weighted least-squares regression, by using the residual errors as covariance information to estimate stiffness gain matrices. A proportional-derivative controller is used to move sequentially towards the sequence of targets (see [26] for details).

During the demonstration phase, the position, velocity, and acceleration of the end-effector are recorded in the robot's frame of reference using forward kinematics. In the forward kinematics model for the arm we have also included a model of the two passive DOF of the sponge for cleaning the surface, in order to improve the precision of recording of the tip of the tool which the end-effector is holding. In order to provide generalization ability for cleaning a surface regardless of its position and orientation with respect to the robot, the recorded trajectories from the robot's frame of reference are transformed to the surface's frame of reference before encoding them.

A demonstration consisting of T positions x (x has 3 dimensions), velocities $\dot{x}$ and accelerations $\ddot{x}$ is recorded by the robot. We use a mixture of K proportional-derivative systems:

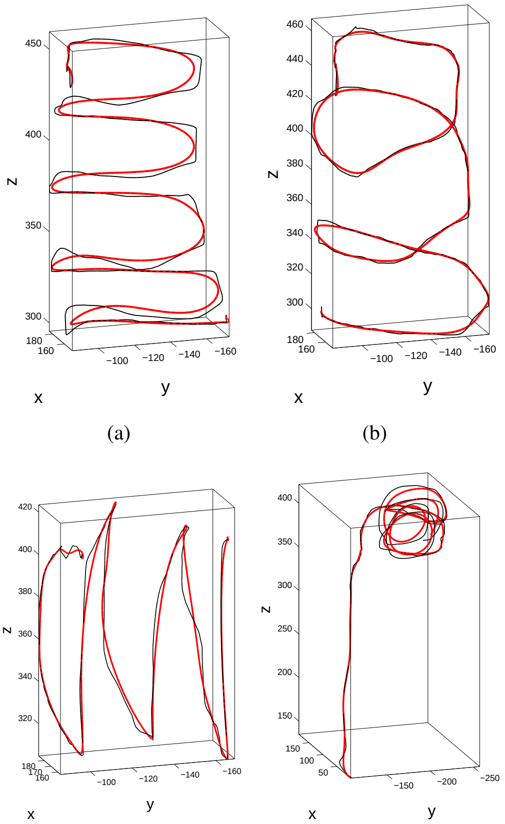
$$\hat{\ddot{x}} = \sum_{i=1}^{K} h_i(t) \Big[K_i^{\mathcal{P}} (\mu_i^{\mathcal{X}} - x) - \kappa^{\mathcal{V}} \dot{x} \Big], \quad (1)$$

where $\mu_i^{\mathcal{X}}$ are the learned virtual attractors, $K_i^{\mathcal{P}}$ - the full stiffness matrix gains, $h_i(t)$ - the mixing weights, and $\kappa^{\mathcal{V}}$ is a damping factor. Fig. 4 shows example for recorded trajectories and their corresponding reproduced trajectories from the learned model representations. Both position and force information are encoded by using this encoding schema (see [27] for details).

C. Reproduction phase

For the reproduction, the learned trajectory is first transformed from the surface's frame of reference back to the robot's frame of reference. Then, a hybrid position/force controller is used. The controller includes forward and inverse kinematics functions for hand position feedback control, an ankle joint regulator to ensure a reference static force component at the initial contact, and a ZMP-based feedback controller for the desired hand force during the

[2]HOAP-2's controller has been modified to ensure 1 ms real-time torque control for all joints.



(a) (b)

(c) (d)

Fig. 4. Demonstrated trajectory (in black) and the learned trajectory (retrieved from the model, in red). Four trajectories are demonstrated for variations of the cleaning task: (a) and (b) cover a bigger area and use smooth movement for the end-effector; (c) uses faster movement with sharp turns; (d) is for spot cleaning, focusing only on a small area.

motion. Note that the force/torque sensor is detached from the hand during the reproduction phase because the robot's arm is underpowered to bear the weight of the sensor while reproducing the task. Because of this, the applied force at the hand is calculated via the ZMP position. The passive two-DOF attachment is used so that the tool in the hand has complete six DOF to comply with the surface being cleaned. The attachment is sensorless, its joint angles and joint velocities are calculated via the kinematic closed-loop condition.

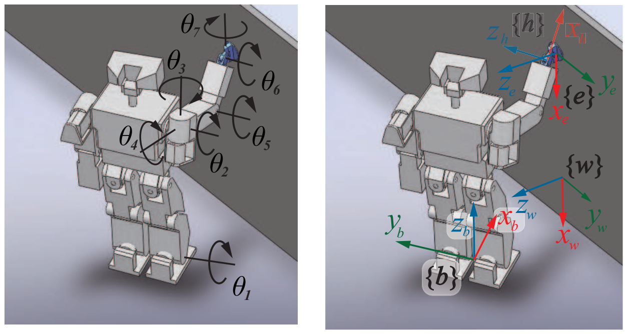
A 3D model of the reproduction phase is shown in Fig. 5. The sagittal and transverse projections of the used robot model are depicted in Fig. 6. The reproduction controller block schema is given in Fig. 7.

III. EXPERIMENTS

A. Experimental setup

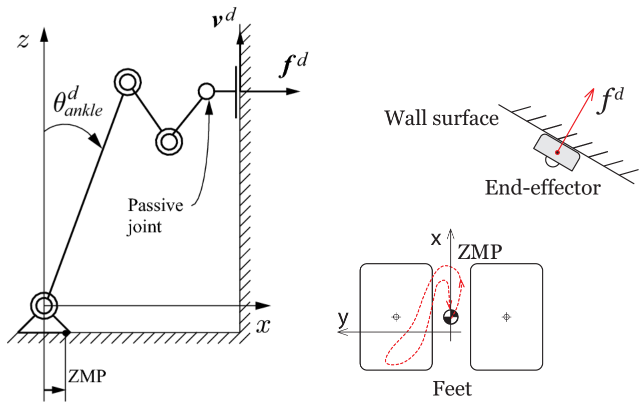
The experimental setup is shown in Fig. 1. The following number of servo actuators of Fujitsu's HOAP-2 robot are used: six for each leg, four for each arm[3], and one for the waist. Four force sensing resistors (FSRs) in each

[3]The left arm is kept fixed during the experiment, at a safe distance from the torso and the legs.



(a) Degrees of freedom (b) Coordinate frames

Fig. 5. 3D model of the reproduction phase. (a) Joint angles θ_1 through θ_5 are actively controlled, θ_6 and θ_7 are the passive joint coordinates resolved via kinematic loop closure. (b) Coordinate frames of reference used for transformation of the trajectories: {b} base, {w} whiteboard, {h} hand, {e} end-effector (sponge).



(a) Ankle torque control (b) ZMP projection

Fig. 6. (a) The model of the robot projected onto the sagittal plane. The notations match those of the controller. (b) Transverse plane projection of the robot's feet and the swept path by the ZMP projection during the reproduction of the task (in red dotted line).

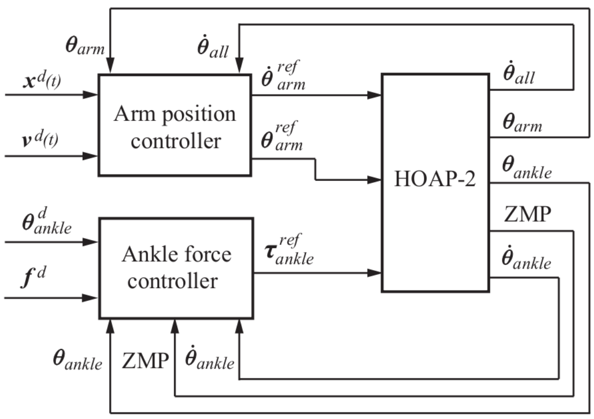


Fig. 7. Block schema of the controller used during the reproduction phase.

foot are used to detect reaction forces from the floor. The exerted force by the sponge on the whiteboard is recorded from a 6-axis Nitta F/T sensor attached to the end-effector during the demonstration phase. Vision is not used. The position and orientation of the whiteboard is computed by touching 3 points of it with the end-effector via kinesthetic teaching. This is a convenient way to adapt to a new position/orientation of the whiteboard when the robot is moved to a new place. Anti-slippery coating is used for the feet to allow exerting stronger forces on the whiteboard without foot slippage.

B. Experimental results

Fig. 4 shows four example recorded trajectories, and their corresponding reproduced learned trajectories. A variety of positional profiles have been successfully encoded with the same number of parameters $K = 50$. The trajectories are sampled to 500 points each, and the reproduction time is between 10 and 30 seconds.

Fig. 8 shows the demonstrated force during the teaching phase on one trial. The demonstrated force required to perform the task is between 10N and 20N (the force component in the direction normal to the surface). During the reproduction, forces in the same range are used (i.e. no rescaling is done) because the robot is able to exert forces of such magnitude using both the ankle torque controller and the gravity force produced by leaning forward. Only the normal (F_z) component of the force is reproduced by the ankle controller, while the other two components are naturally produced by the planar movement of the end-effector along the surface. The force exerted by the end-effector is not measured directly during the reproduction, because the F/T sensor is too heavy to be moved by the robot while in contact with the surface. Instead, the exerted force is derived from the reaction force measured at the feet of the robot, which is shown in Fig. 9.

Fig. 10 shows the learned speed profile of the end-effector for the same example. The maximum speed reaches 400 mm/s, which the robot is capable of reproducing. However, for a faster or more dynamic task, or for a more force-intensive task, appropriate rescaling would be necessary.

A video of the surface cleaning experiment is available online at [28]. Fig. 1 shows some selected snapshots from the demonstration and the reproduction phases.

IV. DISCUSSION

Numerous problems were identified and solved during the experiments. Because of the only 4 available DOF of the arm it was impossible to keep the wrist oriented parallel to the whiteboard. This was solved by using two additional passive DOF in the tool (sponge) and adding the passive joints to the kinematics model of the robot.

The initial robot posture before starting a reproduction turned out to be very important for avoiding self-collisions. Improvements to the current implementation of the inverse kinematics position controller are required to ensure collision-free paths for both the end-effector and the arm.

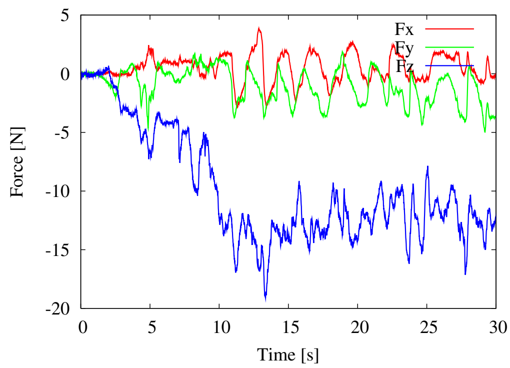


Fig. 8. This shows the demonstrated force during the teaching phase, recorded using a force/torque sensor mounted on the end-effector (the right hand of the robot).

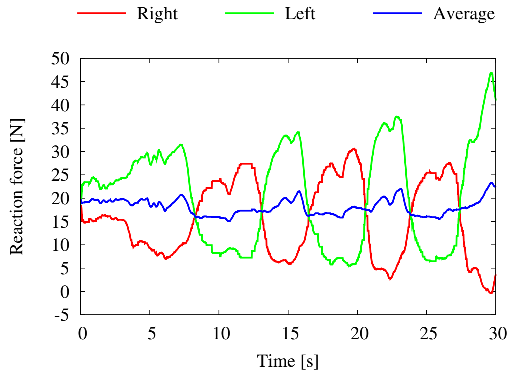


Fig. 9. Reaction force measured at the feet of the robot during reproduction.

A trade-off was established in the compliant controller for the arm. The implemented active control for the arm makes the arm feel ”lighter” while doing kinesthetic teaching, but at the same time it makes it harder to do rapid sharp changes in the velocity. For heavier human-sized humanoid robots, however, it might be necessary to use state-of-the-art gravity compensation controllers to allow easier movements.

The proposed method can be extended in several directions. The Reaction Null Space method can be extended to also include stepping. In case of a strong perturbation, it might be necessary to move one foot forward or backward in order to keep the balance of the robot, which requires online footstep re-planning, which has been studied in the context of robot guidance but not in the context of kinesthetic teaching.

The presented approach is easily applicable to bi-manual

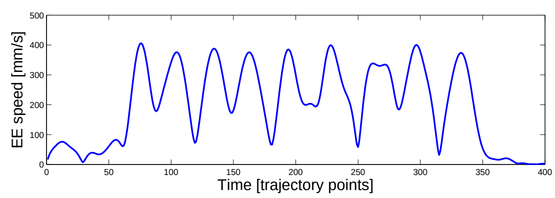


Fig. 10. Speed profile of the end-effector (EE) for the demonstrated trajectory shown in Fig. 4(a).

tasks, due to the relative independence of the lower-body balance controller from the upper-body movements. This allows the human teacher to demonstrate tasks involving both arms such as manipulating big objects, pulling a bar, putting wallpapers, etc. The disturbances caused by the upper-body kinesthetic teaching will be rejected by the Reaction Null Space controller.

In the presented experiment, the generalization abilities of the position and force encoding technique are not fully exploited. They will be used in further work to cope with situations where multiple and noisy demonstrations are available, in which case the model will be used to encapsulate in a probabilistic way the uncertainty in order to generalize over a larger range of new situations.

Another extension that we plan to consider is to incorporate visual feedback to provide the robot with the capability to automatically find spots to clean on the surface, determine their shape and select an appropriate trajectory from the learned movement repertoire.

V. CONCLUSION

We have presented an approach for upper-body kinesthetic teaching of a free-standing humanoid robot, based on imitation learning and disturbance rejection with Reaction Null Space method. We successfully applied it to a surface cleaning task. The proposed approach and its future extensions will secure a more natural way for human-robot interaction.

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