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Humanoid Robot Posture-Control Learning in Real-Time Based on Human Sensorimotor Learning Ability

Luka Peternel and Jan Babič

Abstract— **In this paper we propose a system capable of teaching humanoid robots new skills in real-time. The system aims to simplify the robot control and to provide a natural and intuitive interaction between the human and the robot. The key element of the system is exploitation of the human sensorimotor learning ability where a human demonstrator learns how to operate a robot in the same fashion as humans adapt to various everyday tasks. Another key aspect of the proposed system is that the robot learns the task simultaneously while the human is operating the robot. This enables the control of the robot to be gradually transferred from the human to the robot during the demonstration. The control is transferred based on the accuracy of the imitated task. We demonstrated our approach using an experiment where a human demonstrator taught a humanoid robot how to maintain the postural stability in the presence of the perturbations. To provide the appropriate feedback information of the robot's postural stability to the human sensorimotor system, we utilized a custom-built haptic interface. To absorb the demonstrated skill by the robot, we used Locally Weighted Projection Regression machine learning method. A novel approach was implemented to gradually transfer the control responsibility from the human to the incrementally built autonomous robot controller.**

I. INTRODUCTION

An important goal of robotic research is to integrate robots into our everyday's life where they could either be our assistants or independently perform human everyday tasks. A crucial aspect of the integration is how to pass human skills to the robots in an intuitive and efficient way. Humanoid robots are complex systems and control of such systems is a difficult and multidimensional problem [1]. Construction of classical control algorithms is a challenging and time-consuming task that requires expertise in robotics and programming. Since most of the future users of the robots will not be robotic experts it is crucial that the synthesis of robotic skills is as intuitive and simple as possible.

An alternative approach to the classical control algorithms is the machine learning approach such as *Programing by Demonstration* which is sometimes referred to as *Imitation Learning* [2], [3], [4], [5]. This approach aims to teach robots by providing them with a set of demonstrated examples which are then generalized by one of the machine learning tools [6]. The demonstration offers a more natural interaction with the robot [3]. Besides, a variety of demonstrated examples offer better adaptability which is also a very important aspect of robot control. Since the users have different needs and since the robots will have to work in various unstructured environments it is imperative that the robots are as adaptable to unpredicted changes as possible.

One of the drawbacks of *Programming by Demonstration* is that the teaching procedure is usually divided into several sequential steps. In the first step, the human demonstrator gathers the training data by demonstrating a task to the robot. In the following step, the training data is generalized to form a control algorithm. In the last step, the robot uses this newly obtained knowledge to perform the demonstrated task on its own. Our goal is to make robots learn simultaneously during the demonstration. The motivation for this is to speed up the process and make it more intuitive for lay people. This process is sometimes referred to as *real-time learning* and requires machine learning tools capable of incremental learning. Notable examples of incremental learning algorithms are *Locally Weighted Projection Regression* [7], [8], *Local Gaussian Regression Process* [9] and *Incremental support vector machine* [10]. In classical approaches of *Programming by Demonstration* human demonstrates new tasks to the robot by moving the robot during the demonstration. In these approaches the human is only demonstrating kinematic solutions to the robot while the dynamics of the robot is neglected.

Humanoid robots have a very complex dynamics and a great deal of care is required to keep its posture in a stable position. Algorithms to control robot dynamics are very complex and computationally expensive. On the other hand, humans are extremely adaptable and are able to learn many different tasks throughout their life (posture control, playing sports, using tools, driving vehicles etc). For example, at the very early stage of our life we learn how to maintain our postural stability which allows us to stand and walk. Once we are familiar with our sensorimotor system we are then capable of automatic and intuitive control of the posture while we can simultaneously perform other complex tasks. Our goal as researchers is to use these human abilities for intuitive control of humanoid robots where we would like to teach the robots how to perform the desired tasks autonomously. This approach was previously referred to as *Human Sensorimotor Learning for Robot Skill Synthesis* [11], [12], [13]. The key of this paradigm is to exploit human sensorimotor learning ability [14] to generate autonomous robot controllers. The human can consider a robot as a tool. Much like humans control a hammer, a car steering-wheel or a computer mouse they should be able to control the robot. The process can be seen similar to the teleoperation [15] where human operator first has to learn how to use the feedback information from the haptic interface in order

The authors are with the Department of Automation, Biocybernetics and Robotics, Jožef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia luka.peternel@ijs.si and jan.babic@ijs.si

to successfully operate the machine. The difference is that we wish to transfer human skills to the robot by employing machine learning techniques where both human demonstrator and the robot are mutually learning. In other words, while human learns how to operate the robot, the robot is simultaneously absorbing the knowledge.

Some efforts towards our goal were already made: Oztop et al. used visual feedback to teach a robot how to perform a manipulation task with a robotic hand [11], [12]. Recent studies by Babič et al. showed that the visual feedback is sufficient for handling kinematic problems but proved to be somewhat ineffective for solving dynamical problems [13]. Babič et al. used vestibular and proprioceptive feedback provided by a 6DOF Stewart platform below the demonstrator's feet to control the stability of a humanoid robot modelled as an inverted pendulum. The interface they used was effective in providing an adequate feedback to the human demonstrator but it limited the workspace of the human demonstrator to the size of the platform. In addition, angular movement of the platform limited the possibilities of simultaneous manipulation tasks.

In order to simplify the transfer of the skills from the human to the robot and to provide a natural and intuitive interaction between the human and the robot, we propose a system capable of teaching humanoid robots new skills in real-time. The key element of the system is exploitation of the human sensorimotor learning ability to operate a robot. In order for the robot to learn the demonstrated task simultaneously while the human is operating the robot, we implemented a real-time learning approach. Further, we designed an innovative method that gradually transfers the robot control responsibility from the human to the incrementally built autonomous robot controller. In effect, the robot being initially controlled only by the human demonstrator is automatically acquiring the skill and is becoming gradually independent of the human demonstrator. After some time, the demonstrator's motion has no more effect on the motion of the robot and the robot becomes completely autonomous in performing the desired skill.

II. SYSTEM OVERVIEW

The proposed system aims to simplify humanoid robot control. The emphasis is on the human sensorimotor learning ability and real-time learning. Human is to use the natural capacity to learn in order to perform a specific task with the robot in real time. In this sense, human acts both as an operator and a demonstrator. During the human adaptation the robot should simultaneously absorb the skill that the human is performing on the robot and gradually take over the control over the demonstrated task. This approach imitates the normal training process as observed between human teacher and human learner. When the teacher is demonstrating something to the learner, the learner is imitating the teacher and the skill of the learner is gradually increasing throughout the demonstration. If the accuracy of the learner's imitation is increasing during the teaching then the teacher's involvement into learner's performance of the task is decreasing. On the other side, if the learner's imitation is inaccurate then the teacher intervenes to correct the learner's performance.

To develop this system we had to combine several different elements. The proposed system with its key elements is presented on Fig. 1. The human and the robot are connected with a feedback interface and with a feed-forward interface. The main purpose of the feed-forward interface is to capture and transfer the human motor reactions to the robot motor commands. On the other hand, the feedback interface transforms sensory information from robot's sensors into a form of feedback that stimulates the human senses. In this aspect human sensorimotor system acts as an adaptive controller during the demonstration. The robot absorbs the provided knowledge by learning the human reactions to the given sensory information. We used one of the machine learning algorithms to form the autonomous robot controller based on the training data. The last element is the algorithm that evaluates the accuracy of the robot's imitation and weights the influence of the human and the robot on the performance of the demonstrated task accordingly.

A. *Feed-forward interface*

The feed-forward interface directly maps the human body motion to the robot body motion. For this purpose we used NDI 3D Investigator contactless motion capture system. The system captures the body motion optically by detecting positions of the markers, placed on the human body. The joint angles calculated from the position markers were sent to the corresponding joints of the humanoid robot. Because the human body structure is similar enough to the humanoid robot body structure, we mapped the human joint angles directly to robot join angles. Possible differences are bound to be compensated by the human adaptability and through the sensorimotor system.

B. *Feedback interface*

Feedback sensory information is an important element of the sensorimotor learning. Human learns how to use the available feedback which stimulates the body senses in order to make the appropriate motor reactions. To make the robot control as intuitive as possible, it is reasonable to associate the feedback interface tightly with a task that is already naturally associated by the humans. The main

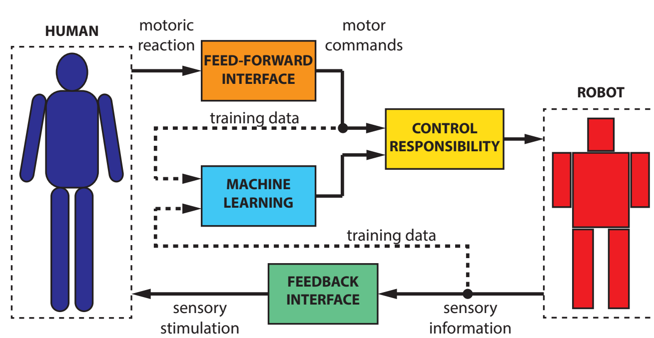

Fig. 1. Schematic presentation of proposed system for teaching humanoid robots new skills in real-time.

factor in mammalian postural control is the centre of mass information [16] that is usually integrated as a combination of the proprioceptive, vestibular and tactile senses. In order to reflect the humanoid robot's postural stability to the postural stability of the human demonstrator, we constructed a special full-body haptic interface that can generate appropriate forces on the centre of mass of the human demonstrator.

The haptic interface [17] used in the experiments is shown in Fig. 2. It consists of two aluminium support frames which are positioned opposite to each other. The human is positioned in-between the support frames. Each support frame carries an electric servo motor. The motors operated in the torque-control mode. Each motor was used to power a winch that pulled the wire connected to the subject through a belt. The belt was strapped around the human waist at the approximate position of the human centre of mass [18]. Two JR3 multi-axis force sensors were used to measure the forces in the wire. Feedback from the force sensors was used to control the desired force applied to the human.

The desired force that acted on the human through the haptic interface and provided the feedback about the state of the robot postural stability was determined using the robot centre of mass information. In order for the human to directly feel the state of the robot postural stability, the same forces should be applied to the human centre of mass as acting on the humanoid robot's centre of mass. The magnitude of the force depends on the position of the centre of pressure which is measured by the force sensors integrated in the robot's feet. The relation between the centre of pressure and the force acting on the human centre of mass was approximated by the inverted pendulum model [19].

C. Machine learning

To learn the mapping between the given sensory information and the appropriate motor reactions we used a machine learning method that generated a function between the input and output pairs from the demonstrated training set of data. In our case the input data was the information about the robot centre of mass obtained from the force sensors in the robot's feet, while the output data were joint angles that the feed-forward interface sent to the robot. Since our goal was simultaneous learning of the robot during the demonstration, we chose an incremental method *Locally Weighted Projection Regression* (LWPR). We chose this method for its speed and effectiveness [6]. Computational complexity of LWPR is $O(n)$, where n is the number of training data. *Local Gaussian Regression process*, on the other hand, would offer better accuracy of the prediction but has a larger computational complexity [9] which could cause problems in speed.

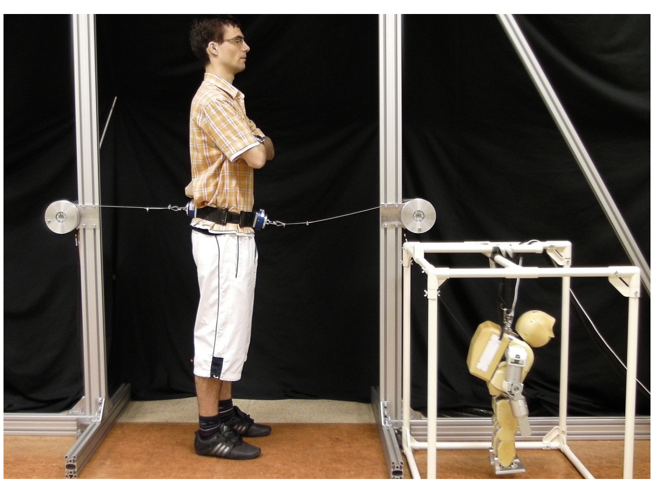

Fig. 2. The developed haptic interface used for providing feedback about the state of the robot postural stability to the human demonstrator.

LWPR is a regression method that offers real-time learning. Compared to a well-known *Gaussian Process Regression* (GPR) [20] which is a global method, LWPR is a local method that divides the training set of data into local subsets. Each subset is approximated by a local model. The prediction is then reduced to selecting one of the previously fitted models, as opposed to GPR where regression must be performed over the entire training set. In the case of LWPR, prediction of output $\hat{y}$ for the given input $\boldsymbol{x}$ is calculated with N number of weighted local linear models. Individual local linear model can be described by

$$\bar{y}_k = \bar{\boldsymbol{x}}_k^T \hat{\boldsymbol{\theta}}_k \tag{1}$$

where $\bar{\boldsymbol{x}}_k^T = [(\boldsymbol{x} - \boldsymbol{c}_k)^T, 1]^T$, $\boldsymbol{c}_k$ is the centre of k-th local region and $\hat{\boldsymbol{\theta}}_k$ is a vector that consists of the parameters of the k-th model. The influence of the individual local model on the prediction is defined by the weights that are characterized with a Gaussian kernel:

$$w_k = exp\big(-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{c}_k)^T \boldsymbol{D}_k (\boldsymbol{x} - \boldsymbol{c}_k)\big) \tag{2}$$

where $\boldsymbol{D}_k$ is a distance matrix, containing information about the size and shape of each local model. Prediction $\hat{y}$ is a sum of contributions of all local linear models $\bar{y}_k$, weighted by w_k

$$\hat{y}(\boldsymbol{x}) = \frac{\sum_{k=1}^{N} w_k \bar{y}_k(\boldsymbol{x})}{\sum_{k=1}^{N} w_k} \tag{3}$$

Both $\boldsymbol{D}_k$ and $\hat{\boldsymbol{\theta}}_k$ are updated during the learning process when the new training data is received.

D. Control responsibility transfer

During human training it is expected that the learner gradually takes control of the performance of the demonstrated task. We call such shifting of the control as the transfer of the *control responsibility*. The control responsibility should depend on how successfully the demonstrated task can be imitated by the learner. At the point when the learner is considered trained and fit to perform the task on its own, the teacher should withdraw and the training process should conclude. To achieve this process, we need an appropriate measure for the accuracy of the imitated task and a criterion that determines when the learner is fit to perform the demonstrated task on its own. In our case the learner is represented as an autonomous robot controller that is learning by the machine learning algorithm.

We solved these two requirements by developing an algorithm that monitors the error between the action demonstrated by the human and the action that would be imitated by the autonomous robot controller. Monitoring the error at each sample time does not provide a useful measure since any meaningful action or body movement usually last several hundred sample times. Hence we rather considered an error over a certain period of time. We call this time interval as *the evaluation period* T. The evaluation period mainly depends on the task. In the case of a reaching task, this evaluation period should be variable and defined as the time of each demonstrated hand movement (trajectory). On the other hand, posture control task does not have a specifically defined length of the action so the evaluation period can be constant. Nevertheless it should be long enough to make for a sound comparison. To measure the difference between the human action and the imitation by the robot controller, we decided to use *Mean Square Error*. MSE of evaluation period T_j is

$$MSE_j = \frac{1}{N_j} \sum_{i=1}^{N_j} (\hat{y}_i - y_{Hi})^2 \tag{4}$$

where $\hat{y}_i$ is the output predicted by LWPR in the i-th sample of the j-th period T, y_{Hi} is the human output in the i-th sample and N_j is the number of samples in the j-th period T.

The criterion that determines the influence of the teacher on the robot task performance was realized by comparing the MSE of the entire demonstration to that point with the maximum MSE over any period T to that point. This criterion is described as

$$C = \frac{MSE_{prev}}{MSE_{max}} \tag{5}$$

where C is the selected criterion, MSE_{prev} is the MSE of all previous samples and MSE_{max} is current maximum MSE of any period T. Criterion C weights the influence of the human and the robot controller during the training process in the following manner:

$$y_{ctrl} = y_H C + \hat{y}(1-C) \tag{6}$$

where y_{ctrl} represents the control signal composed of the motor commands sent to the robot joints.

To determine when to conclude the demonstration phase and make robot operate autonomously we selected a criterion which compares the current MSE over the period T with the minimum MSE over any period T to that point. If MSE fails to improve with regard to the minimum MSE than the *fail count* is increased by one. When the fail count reaches a predefined value, the training process is stopped and the human demonstrator is removed from the system. As a consequence, the robot is controlled solely by the autonomous controller derived by the machine learning algorithm based on the human training data.

III. EXPERIMENTS AND RESULTS

We evaluated the proposed system with an experiment where a human demonstrator taught a humanoid robot (Fujitsu HOAP-3) how to counteract external postural perturbations and keep its postural stability in the sagittal plane. The experiment is shown in the *attached video*. The motion of the human demonstrator was mapped to the humanoid robot in real time. Simultaneously, the state of the robot's postural stability was fed back to the human demonstrator through the haptic interface, described in the previous section. The assistant that was positioned near the robot produced random perturbations of the robot's posture by pushing or pulling the robot in different directions. The perturbations caused changes of the robot's centre of mass which were detected by the pressure sensors at the feet of the humanoid robot. As a consequence, the human demonstrator felt the equivalent forces at his/her own centre of mass and reacted instinctively by moving the body to compensate for the perturbations.

Experiments showed that, in most cases, the human reacted with the so called *hip strategy* [21], [22]. This means that the human compensated the perturbations at the centre of mass by mainly moving in the hip and ankle joints. Based on this we decided to use only the robot hip and ankle joints for this task.

In the first phase of the experiment the human demonstrator had to familiarize himself/herself with the haptic interface and the feedback it provided. Because the haptic interface stimulated senses that humans use for their own postural control, the subjects adapted to the feedback relatively quickly (a few minutes). We scaled the gain factor of the haptic interface so that the exerted force felt by the demonstrator's body was as comfortable and yet as efficient as possible. The output force of the haptic interface must not be too high for two reasons. The first reason concerns safety; to prevent the risk of falling, the interface must not pull the human too hard. The second reason is of operational nature; the movement of the human demonstrator within the interface should not be constrained therefore the maximum force must be low enough for the human body to be able to overcome it.

Fig. 3 shows the human motor reactions to the changes of the robot's centre of pressure caused by the external postural perturbations. The changes of the centre of pressure as detected by the force sensors in the robot feet are shown on the upper inset. The green area represents the stable area that is defined by the convex polygon of the robot feet (support polygon). If the robot's centre of pressure moved outside of the support polygon the robot would fall. We can see that the human operator was able to keep the centre of pressure of the robot within the stable limits during the whole demonstration process. The lower inset shows the reactions of the human demonstrator that kept the robot's centre of pressure inside the stable region. The green line represents the ankle joint motion while the red line represents the motion in the hip joint. The human reacted to the changes of the robot's centre

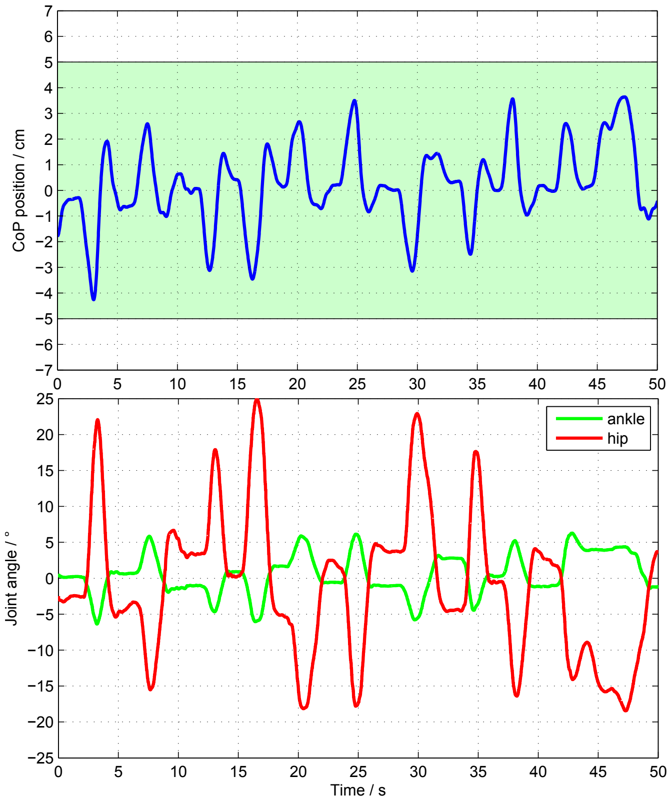

Fig. 3. Human reactions to the change of the robot's centre of pressure. Blue plot in the upper inset represents changes of the robot's centre of pressure where the green zone represents the statically stable region. The lower inset shows human reactions to the changes of the robot's centre of pressure. The green plot represents the ankle joint motion as measured by motion capture system while the red plot represents the motion of the hip joint.

of pressure by rotating the ankle joint in the direction of the change and by the rotation of the hip joint in the opposite direction of the change. Due to the kinematics of the human body, the magnitude of the angular change in the hip joint was significantly larger than in the ankle joint.

There was a noticeable difference between the magnitudes of the human hip reactions in the frontal and posterior directions. There are two possible reasons for this. One is the limited movement of the human upper body in the posterior direction and the other is the structure of the human foot. The human ankle joint is located posteriorly to the centre of the foot. Hence, the portion of the support polygon in front of the ankle joint is significantly larger than the portion of the support polygon posteriorly to the ankle joint. On the other hand, the humanoid robot has the ankle joints located approximately in the centre of its feet which makes the support polygon equally distributed around the ankle joints.

The upper inset on Fig. 4 shows the human hip movements during the experiment. The black line represents the hip joint control signal received by the robot. This signal is composed of the weighted hip angle reaction of the human demonstrator and the predicted angle reaction obtained from the incrementally built autonomous robot controller. The blue area represents the part of the motion that was contributed by the human demonstrator and the red area represents the predicted output produced by the LWPR algorithm. The contributions of the human demonstrator and LWPR algorithm were determined using the criterion C. We can see that the autonomous robot controller is gradually taking over the responsibility of maintaining the robot's postural stability (portion of the red area is increasing) while the influence of the human demonstrator is gradually fading out (portion of the blue area is decreasing). At the beginning of the demonstration, the human demonstrator had full control over the robot (the signal sent to the robot is equal to the human motion represented by the blue area). As the demonstration progressed and the LWPR algorithm was learning, the control responsibility was gradually shifted to the robot. When the learning of the robot controller was completed, the demonstrator's influence was ignored and the demonstrator was removed from the training process. As a consequence, the robot entered into the phase of autonomous operation (the signal sent to the robot is equal to the output of the autonomous robot controller represented by the red area). As indicated in the lower inset of Fig. 4 that shows the value of the criterion C during the demonstration, this happened after 65 seconds when the human influence fell to zero. After that moment the control signal sent to the robot is equal to the predicted value of the autonomous robot controller.

IV. CONCLUSIONS

In this paper we presented a novel approach for teaching humanoid robots new skills. The main paradigm of the approach is using human sensorimotor learning ability to operate the robot and transfer the gained knowledge to the robot. The training procedure was done in real-time where the control responsibility was gradually transferred from the human demonstrator to the robot based on how successful the robot was in imitating the demonstrated task. The algorithm that determined this responsibility removed the human from the system once the robot was considered suitable to operate on its own. We demonstrated this approach using the experiment on HOAP-3 humanoid robot where the human demonstrator successfully taught the robot how to counteract external postural perturbations.

For the purpose of providing the human with the necessary feedback information about the robot's stability we designed and utilized a full-body haptic interface which mapped robot's postural stability state to the human tactile and proprioceptive senses. The feedback from this haptic interface proved to be sufficient for the human to make the appropriate motor commands that kept the humanoid robot postural stability throughout the demonstration. The limitation of the current haptic interface is that it can provide the feedback only in sagittal plane.

In the future we will try to upgrade the haptic interface to increase the dimensionality of the feedback. We will work towards extending this approach to teach humanoid robots how to perform other more complex tasks that include more degrees of freedom. Since postural stability is a basic element

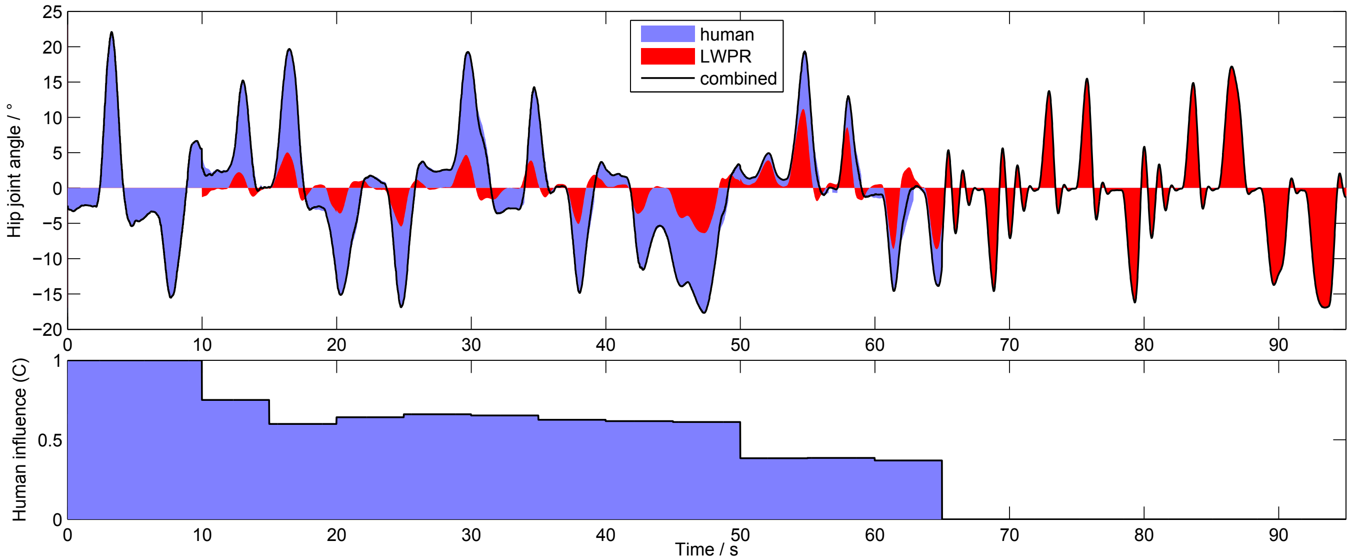

Fig. 4. Gradual transfer of control responsibility during the demonstration. Upper inset shows the hip joint control signal received by the robot (black plot) throughout the experiment. This signal is composed of the weighted hip reaction of the human demonstrator (blue area) and the predicted angle reaction obtained from the incrementally built autonomous robot controller (red area). Lower inset shows the gradual decrease of the human demonstrator's influence on the motion of the robot C at different intervals.

of almost every full-body task, it was chosen to be our first step. When performing tasks such as walking or manipulation, the postural stability must be maintained intuitively and simultaneously during the operation. In addition to teaching the robots new tasks, we will try to improve the algorithms associated with the transfer of control responsibility during the demonstration. We will also try to address the issue of attribution. If the task performance at certain point is not successful we want to know whether the human demonstrator or the robot was responsible for it.

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