Development of a Robotic Teaching Interface for Human to Human Skill Transfer

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Abstract—The tutor-tutee hand-in-hand teaching may be the most effective approach for a tutee to acquire new motor skills. Repetitive nature of such procedures in a group setting usually results in a high labour cost and time inefficiency. Potential solution can be utilizing robotic platforms playing the role of tutors for demonstrating and transferring the required skills. This requires an appropriate guidance scheme to integrate the tutor’s motor functionalities into the robot’s control architecture. For instance, for hand-in-hand supervision of the writing task, the tutor’s corrections can be applied when necessary, while a very compliant motion can be achieved if no errors are detected. Inspired by this behavior, we develop a teaching interface using a dual-arm robotic platform. In our setup, one arm is connected to the tutee’s arm providing guidance through a variable stiffness control approach, and the other to the tutor to capture the motion and to feedback the tutees performance in a haptic manner. The reference stiffness for the tutors arm stiffness is estimated in real-time and replicated by the tutees robotic arm. Comparative experiments have been carried out on a dual-arm Baxter robot. The results imply that the human tutor is able to intuitively transfer writing skills to the tutee and also show superior learning performance over some conventional teaching by demonstration techniques.

I. INTRODUCTION

The increasing speed of the development of technologies and tools demand our human users to acquire new motor skills more frequently. In this direction, taking a long training process is usually inevitable to update motor behaviours for most trainees. To improve time efficiency of tutor who perform repetitive training on tutees, computing technology has been introduced, such that once the motor skills have been captured by a computer, it will then work to transform the motor behaviours of all the tutees by itself. A two-step approach was proposed in [1] for transferring skill from tutor to tutee. The tutor’s strategies was abstracted into a sensory-based computational model firstly, and then the online advice was generated for the less-skilled tutees. Neural network was used to extract human skills computationally in [2], and tests on human driving simulator showed potentials of skill transfer from human tutor to many tutees without increasing consumption of time.

As a matter of fact, motor skills are generally difficult to model because of their complexities and unknown elements, despite the advances in neuromotor studies. Therefore, personalized physical guidance provided by the tutor is still the most preferred approach for skill acquisition training [3], particularly, hand-in-hand guidance seems to be most helpful and effective method. Examples include parent hand-in-hand teaching a kid learning calligraphy, and physician guiding the rehabilitation movements of a stroke patient. A robot system can be used to replace human tutor by recording tutor’s customized physical guidance to a particular tutee, and carrying on the repeatative training without the tutor’s effort, to greatly reduce manpower cost. To enhance teaching and learning experience through a robot, a visual/haptic training display system was proposed in [3] during human-robot-human training. Both force and motion control were considered in [4] for human-robot-human skill transfer which mimicked the human learning proceedings in a compliant way.

In this work, our aim is to explore the potential of the robotics technology for human to human skill transfer by enhancement of teaching and learning experience. Our work focuses on the development of a robotic interface that is capable of capturing the tutor’s guidance control and to better provide learning performance feedback. As we know, hand-in-hand guidance control is similar to tool using tasks, which rely on mechanical impedance adaptation during interaction for disturbance attenuation and minimization of tracking errors as well as regulation of interaction force [5]. To imitate human’s variable impedance control strategy, investigation has been made on impedance learning based on natural motor skills [6], [7]. A human like adaptive impedance algorithm was developed in [8] together with adaptation of force. A learning framework to encode and reproduce impedance behaviours using a task-parametrized statistical dynamical system was developed in [9].

It is ideal to copy human tutor’s variable impedance to a robot, but the conventionally distractive impedance identification approach is not applicable to natural human robot interaction. Fortunately, non-distractive stiffness estimation can be realized by using surface Electromyography (sEMG) signals. Successful applications can be found in [10], [11], [12], [13]. Instead of directly estimating arm endpoint stiffness [10], [11], [12], estimating stiffness variation was proposed in [13] to compensate for the effect of nonlinearity. Considering that the arm posture also contributes signif-
icantly to the arm end point stiffness, configuration dependent stiffness has been investigated in [14], [15], and was combined with the effect of muscular co-activation on the Cartesian stiffness profile. In this work, we use IMU reading and human robot coupling to estimate the 7 joint angles of the human arm to obtain pose configuration. sEMG signals are used to extract muscle activations from EMG signals. Based on the evidence from human neuromotor control experiment, muscular co-activations contribute to a coordinated regulation of the task stiffness in all directions, a novel model of the arm endpoint stiffness was proposed using only a single pair of muscles [16]. This computationally efficient model will be employed in this work together with arm configuration reconstructed from IMU readings to estimate arm end point stiffness. Both IMU sensor and sEMG sensor used in this work are the built in sensors in the commercial MYO armband (Fig. 1) that is worn by the human tutor. MYO armband is is equipped with an eight-channel sEMG sensor and a nine-axis IMU sensor.

The main contribution of this work lies in the development of an intuitive and efficient teaching interface using a bi-manual robot platform which provide configuration similarity between the two arms. A virtual connection between the two arms is established to enable the tutor “feel” the performance of the tutee in a haptic manner, similarly as the hand-in-hand training. In the presence of the virtual connection channel, a stiffness-force feedback approach is integrated to enhance stability of the teaching interface. No a priori training is required for either tutor or tutee, and after a few initial training iteration, robot supervised training would take over the tutor supervised training to greatly reduce manpower cost and to increase efficiency.

II. HUMAN ARM ENDPOINT STIFFNESS ESTIMATION

A. Modelling and Identification of Human Arm Stiffness

Human arm stiffness is contributed by three components: muscle co-contraction activity, arm posture and stretch reflexes [17], [18], which can be synergized in the presentation of Cartesian (endpoint) or joint stiffness. Without considering muscle or posture redundancy, the synergy based simplified stiffness model can be described as below [16]

\[ K_c = J_h^T(q_h)[K_f - \frac{\partial J_h^T(q_h)f_{ex}}{\partial q_h} - \frac{\partial \tau_g(q_h)}{\partial q_h}][J_h(q_h)] \]  

(1)

where \( q_h \in \mathbb{R}^7 \) is a vector of arm’s 7 joint angles, \( J_h(q_h) \in \mathbb{R}^{6 \times 7} \) is arm Jacobian matrix, \( K_c \in \mathbb{R}^{6 \times 6} \) is the end point stiffness, \( K_f \in \mathbb{R}^{7 \times 7} \) is joint stiffness, \( \tau_g(q_h) \) is a vector of gravitational torques and \( f_{ex} \in \mathbb{R}^6 \) is the external force applied onto the endpoint. Obviously, human endpoint stiffness mainly depends on posture which is represented by the Jacobian matrix, as well as joint stiffness and gravity and motion. In this work, the arm joint angles \( q_h \) of the tutor will be estimated using readings from the gyroscope built in the IMU sensors worn on the tutor. Accordingly, the Jacobian matrix \( J(q_h) \) can be calculated using arm length measured beforehand. According to [19], [16], we assume joint stiffness \( K_f \) can be represented as multiplication of an intrinsic constant stiffness \( \bar{K}_f \) identified at the condition of minimal muscle co-contractions and an indicator of the coordinated muscle co-contraction, namely \( \alpha(p_h) \), whereas \( p \) is an indicator of muscle activation level to be specified below.

\[ K_f = \alpha \bar{K}_f \]

\[ \alpha = 1 + \frac{\beta_1[1-e^{-\beta_2p}]}{[1+e^{-\beta_2p}]} \]  

(2)

where \( \beta_1 \) and \( \beta_2 \) are constant coefficients to be estimated, and \( p \) is calculated in the following manner. First, low pass filtering and moving average techniques are used to extract an envelop of the raw sEMG signals from each of the 8 channels using algorithm shown in Fig. 2. The moving average process takes the following equation

\[ f(A_t) = \frac{1}{W} \sum_{k=0}^{W-1} EMG(A_{t-k}) \]  

(3)

where \( f(A_t) \) is enveloped sEMG amplitude, \( W \) is the window size, \( EMG(A_k) \) is the sEMG signal amplitude at sample point \( k \), and \( t \) is the current sampling time. The absolute value of enveloped sEMG amplitude from each of the \( N = 8 \) channels is then summed together to yield an indicator of coordinated muscle activation level as defined below

\[ p(k) = \sum_{i=1}^{N} |f_i(A_t)| \]  

(4)

The unknown parameters \( \beta_1 \) and \( \beta_2 \), as well as constant intrinsic joint stiffness matrix \( \bar{K}_f \) is identified based on the following minimization task

\[ \min \| \alpha(p)\bar{K}_f - \frac{\partial J_h^T(q_h)f_{ex}}{\partial q_h} - J_h^T(q_h)K_cJ_h(q_h) \| \]  

(5)

which is derived from (1) by omitting the effect of gravity due to the arm rest used in the experiment. In order to obtain the end point stiffness \( K_c \) at different postures, we follow the procedure developed before in [12] to identify a force and position deformation mapping defined below:
Fig. 2: Filtered EMG envelope by using low pass filter and moving average method.

\[
\begin{bmatrix}
  f_x \\
  f_y \\
  f_z \\
\end{bmatrix}
= 
\begin{bmatrix}
  G_{xx} & G_{xy} & G_{xz} \\
  G_{yx} & G_{yy} & G_{yz} \\
  G_{zx} & G_{zy} & G_{zz} \\
\end{bmatrix}
\begin{bmatrix}
  \Delta x \\
  \Delta y \\
  \Delta z \\
\end{bmatrix}
\]  

(6)

where \( f_x, f_y, \) and \( f_z \) are forces generated by robot arm and applied on arm end point along \( x, y, z \) axis, respectively, \( G_{xx} \) is a second-order impedance model, \( \Delta x, \Delta y, \Delta z \) are the deformation caused by the applied force.

B. Identification of Human Arm Posture Based on IMU

As shown in Fig. 3, in this work the human arm is modeled of 7 degree of freedom (DOF) with 3 DOF on the shoulder, 2 DOF on the elbow and 2 DOF on the wrist. Motion tracking using vision sensors [20] may be significantly affected by occlusion during human robot physical interaction. Therefore, in this work to measure arm angles we employ filtered IMU readings, based on the assumption that operator’s body and should are stationary. As shown in Fig. 4, two IMU sensors are worn on the arm, whereas the first one on upper arm close to the shoulder and the second one on the forearm close to the elbow. They are employed to estimate the first 5 joint angles consisting 3 shoulder angles and 2 elbow angles, according to the method in [21]. To calculate the rest 2 wrist angles, we perform simple inverse kinematics using the robot endpoint orientation, because end points of human arm and robot arm are physically coupled. The joint angle estimation method is summarized in Fig. 5.

C. Haptic Feedback to the Human Tutor

In addition to visual feedback, it is better to also provide haptic feedback to the human tutor, such that the tutor’s observation and perception of the performance of the tutee happen in an intuitive manner. In this work, a dual arm Baxter robot is used, and the two robot arms have exactly same kinematics and dynamics. The master arm is connected to the human tutor, and the slave arm to the tutee. The motion tracking error between master arm and slave arm will be used to generate a force feedback applied on the master arm. This force feedback would enable the human tutor to adjust stiffness naturally as if the tutor and the tutee are hand in hand. On the hand hand, given an equilibrium posture specified in joint space for the master arm, stiffness feedback is also implemented to tune the restoring force. The stiffness feedback on the master arm improves stability in
practice in the presence of gravity effect, and also stimulates tutor’s muscle activation for awareness enhancement.

As shown in Fig. 6, a virtual impedance model is employed to produce a feedback force based on motion tracking error between the master robot arm connected to tutor and the slave robot arm connected to tutee. Let $D_f$ and $K_f$ be the desired damping and stiffness, $x_m$ and $x_b$ be the velocity and position of master arm end point; $\dot{x}_s$ and $x_s$ be the velocity and position of the slave robot arm. The force feedback to the master arm, namely $F_m$, can then be calculated as below:

$$ F_m = D_f(x_m - x_b) + K_f(x_m - x_b) $$  \hspace{1cm} (7)

Then we transferred it into joint space:

$$ \tau_{mf} = J_f^T F $$  \hspace{1cm} (8)

where $J_f$ is the Jacobian matrix of the robot arm.

To compensate for the effect of gravity on the master arm as well as to improve motion stability, an equilibrium posture $q_0$ is specified and a restoring torque vector $\tau_{ms}$ is generated by an impedance controller implemented on the master arm, as if there are springs and dampers attached to the master arm to bring it back to the equilibrium posture. The $\tau_{ms}$ is defined as below:

$$ \tau_{ms} = D_m\dot{q}_m + K_m(q_m - q_s) $$  \hspace{1cm} (9)

where $\dot{q}_m$ and $\dot{q}_m$ are master arm joint angles and angular velocities, $q_s$ is a predefined equilibrium posture such that the master arm tends to restore back to this posture once released from the coupling with human tutor. The variable diagonal stiffness matrix $K_m \in \mathbb{R}^{7 \times 7}$ is set according to feedback error such that

$$ K_{mi,i} = K_{0i,i} \left(1 - \frac{1}{e^{\|q_{m,i} - q_{s,i}\|} + 1}\right) $$  \hspace{1cm} (10)

where $q_{m,i}$ and $q_{s,i}$ are the $i$th joint angle of the master arm and of the slave arm, respectively. The damping matrix is set as

$$ D_m = \sigma K_m $$

with a properly chosen scaling factor $\sigma$. The stiffness-force feedback $\tau_{ms}$ not only help to maintain stability, but also reinforce tutor’s awareness of the tutee’s performance. The total torque control on the master arm is thus defined as below:

$$ \tau_m = \tau_{mf} + \tau_{ms} $$  \hspace{1cm} (11)

**D. Tracking Control for Human Tutee**

To drive the slave arm tracking the master arm such that the tutee follows the tutor, a PD controller with variable gains is employed on the slave arm as below

$$ \tau_s = D_s(\dot{q}_m - \dot{q}_s) + K_s(q_m - q_s) $$  \hspace{1cm} (12)

where $D_s = \sigma_s K_s$ with a properly chosen scaling factor $\sigma_s$, and the variable stiffness $K_s$ is set according to stiffness of human tutor arm as below

$$ K_s = \sigma_s J_h^T J_s $$  \hspace{1cm} (13)

where $\sigma_s$ is a properly chosen scaling factor, and the tutor’s arm end point stiffness $K_c$ is calculated by

$$ K_c = \alpha(p)J_h^T \bar{K}_f J_h $$  \hspace{1cm} (14)

where $\alpha(p)$ is obtained from (4) and $\bar{K}_f$ is identified by minimization problem specified in (5).

**III. EXPERIMENTAL STUDIES**

**A. Experiment Setup**

To human-robot-human writing skill transfer is implemented on a Baxter Robot to perform comparative tests under four different setups as specified in Table I. Baxter robot left arm is regarded as mater arm with a pen mounted, while the right arm is regarded as slave arm grasped by the tutee who is physically guided by the arm. Two MYO sensors are worn on the tutor: one on forearm close to elbow, and the other on upper arm close shoulder. As illustrated in Fig.7, the MYO sensors are used in this work to measure both muscle activation level indicator $\alpha(p)$ and arm posture.

**Fig. 6:** Illustration of haptic feedback system: the force feedback to tutor is generated by a fixed virtual impedance model “connected” in between the master and slave arms; the stiffness feedback is produced by a variable virtual impedance model “connected” in between the master arm and a specified equilibrium posture.

**Fig. 7:** Profile of signal collection and processing from the MYO sensor.
In the experiment, human tutor is supposed to teach tutee to write a Chinese character “Shui”, under 4 comparative tests as indicated in Tab. I. The experimental system is shown in Fig. 8 (right). Human tutor’s right hand holds a pen assembled on the endpoint of Baxter left arm (master arm), and the right arm (slave arm) physically guide the tutee to write in the three tests.

<table>
<thead>
<tr>
<th>Test item</th>
<th>EMG</th>
<th>stiff-force feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test I (soft mode)</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Test II (rigid mode)</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Test III (sEMG mode)</td>
<td>√</td>
<td>×</td>
</tr>
<tr>
<td>Test IV (sEMG &amp; haptic feedback)</td>
<td>√</td>
<td>EMG stiff-force feedback</td>
</tr>
</tbody>
</table>

Fig. 8: Setup of human-robot-human writing skill transfer: robot left arm (master arm) provides force and stiffness feedback to human tutor and captures the motion, which is transferred to the robot right arm (slave arm) which is identical to the left arm in terms of kinematics. Human tutee is physically guided by the right arm, which is controlled with variable stiffness generated according to the human tutor’s muscle activations.

Fig. 9: Experimental results of the writing performance under four control modes.

**B. Test Results**

The experimental results of writing performance at each stage is illustrated in Fig. 9. The processed EMG signals during different stages are shown in Fig. 10. In the teaching stage, the force and stiffness feedback provides a natural perception of tutee’s performance to the tutor, as if they are connected. This “connection” in fact disturbs the normal writing performance of the tutor, who must respond with adaptation of force and stiffness in order to perform the writing as normal. The response of tutor is unique according to different characteristics of tutee’s motor behaviors, thus a personalized guidance can be provided to tutee. In this work, we evaluate the writing performance in terms of hand trajectory and stiffness adaptation.

One tutor (aged between 20-30) who is good at Chinese handwriting and one tutee without any knowledge of Chinese handwriting participated in the tests under different setups as specified in Table I. Analysis of test results mainly will be performed by comparison of the results under different modes, as shown in Fig.11, where the test results under different modes are indicated using different colors as explained in the bottom of the figure.

(i) Soft mode: Hand writing guidance to tutee is provided by a low gain controller, whereas the control gains are properly chosen to enable the robot performing tasks with low position error as well as contact force. There is no haptic feedback from tutee to tutor such that visual feedback is the only means for tutor to evaluate the performance of tutee. In terms of both motion tracking error and motion error variance, soft mode perform worst.

(ii) Rigid mode: Hand writing guidance to tutee is provided by a high gain controller with control gains properly selected with guaranteed stability. There is no haptic feedback, and similarly to Test (i), the tutor only observes the tutee’s performance using vision. It performs best in terms of motion tracking and tracking variance. However, using a fixed high gain control is brutal and does not provide assistance to the tutor in a personalized manner according to individual tutee’s motor performance. As shown in the analysis of forces, there is low correlation between forces of the master arm (feedback force) and of the slave arm (driving force). When the tutee is able to actively follow the
Fig. 11: Evaluation of the teaching interface for human to human writing skills transfer under four control modes.
tutor’s motion, the guidance force should be reduced to encourage the self-drive motion. But under Rigid mode, the tutee receives large force constantly. 

(iii) sEMG mode: Hand writing guidance to the tutee is provided by a controller of variable stiffness, to be set by the muscle activations of the tutor in the presence of any haptic feedback. The tracking performance of tutee has been greatly improved in comparison with Test (i) under soft mode. In addition, there is a significant correlation between force feedback to tutor and the force driving tutee, implied the teaching adapts to the performance of learning. However, adaptation of muscle activation using only visual feedback is not as natural as in the presence of interactive force, thus the teaching experience is not guaranteed.

(iv) sEMG and haptic feedback mode: Hand writing guidance to tutee is provided by a controller of variable stiffness, to be set by the muscle activations of the tutor in the presence of haptic feedback, which provides an intuitive perception of the tutee’s performance. Similarly to the sEMG mode in Test (iii), the correlation between driving force on the slave arm for tutee and feedback force on the master arm on the tutor is obvious. While in terms of tutee’s tracking performance as well as tracking variance, it out performs the results under the sEMG mode without haptic feedback in Test (iii). Haptic feedback make it much easier for the tutor to adapt muscle activation as a response to the tutee’s performance. Thus, teaching experience is much improved, in addition to the improved learning performance.

IV. CONCLUSION

In this paper, we have developed a robotic interface for human-robot-human skill transfer with improved teaching and learning experience. Human tutor is able to perceive the performance of tutee in both visual and haptic manner, using force feedback ans stiff-force feedback based on tutor-tutee tracking error. Complete capture of the tutor’s skill includes variable stiffness has been realized using a combination of IMU and sEMG signals. Comparative results show that the proposed method is more effective in terms of guidance provided for the tutee and ease of teaching for the tutor in human-robot-human skill transfer experiment. In the future work, more comprehensive tests with multiple subjects will be carried out to further validation the proposed interface.

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