Intention-Driven Variable Impedance Control for Physical Human-Robot Interaction

Yingxin Huo, Xiang Li, Xuan Zhang, and Dong Sun

Abstract—The technology of physical human-robot interaction (pHRI) aims to combine the advantages of both humans and robots, and it is now playing a significant role in many industrial and medical applications. However, the open issues of safety and efficiency have not been systematically addressed in pHRI. In this paper, a new intention-driven variable impedance controller is proposed for compliably-driven robots, where the robot is controlled to track the estimated human motion intention under a variable desired impedance model. The human motion intention is represented with the desired angle of the human limb and approximated with adaptive neural networks (ANNs). Then, the impedance parameters are adjusted online according to the offset between the desired angle and the current joint configuration of the robot. Such a formulation allows the robot to predict human behavior for better collaboration and hence improve the safety and the efficiency of pHRI. The stability of the closed-loop system is rigorously proved with Lyapunov methods, and experiments on a lower-limb exoskeleton are conducted to evaluate the performance of the proposed controller.

I. INTRODUCTION

Research related to pHRI has received high attention in recent decades. It is known that both humans and robots have their advantages and disadvantages for each other. For example, humans are skillful, smart, and highly intelligent, but they have limited payload capacity and limited positioning and tracking accuracy. As a comparison, robots have a high payload capacity and also good position and tracking accuracy, but they are not skillful and have insufficient intelligence. The technology of pHRI can combine the advantages of both humans and robots and hence can play a significant role in many industrial and medical applications [1]–[5].

To achieve a safe and efficient pHRI, two main problems should be considered and addressed. That is, understanding the human motion intention, and controlling the robot to act intelligently to suit it. Various methods have been proposed to estimate or model human motion intention. One way was to measure the muscle activity of the human body [6] or the brain activity [7], [8] with EMG or EEG sensors, then the sensor outputs were directly mapped into the motion intention under the data-driven framework. This method has been implemented in the intention-driven control of Hybrid Assistive Leg (HAL) [9]. The Hidden Markov Models (HMMs) were also used to represent the human motion intention as a series of behavioral sequences [10], to deal with the model uncertainty and explore the hidden intent and thoughts [11]. In addition, the human motion intention was represented as the desired position in the impedance model of the human limb [12]–[14], where adaptation laws were developed to update the unknown parameters of the impedance model and hence eliminate the requirement of training or identification beforehand.

In parallel, many control methods have been proposed to regulate the robot’s actions during pHRI. To deal with unexpected impacts, proxy-based approaches were introduced in [15] to allow the robot to return smoothly to the desired trajectory after the impacts. By observing the human motor behavior, a biomimetic adaptive controller was proposed in [16], to mimic the way the human adapts to forces to deal with the interaction with the environment. An adaption method was proposed for human-robot collaboration [17] to adjust the robot’s role to lead or follow the human. In [2], [18], multi-modal controllers were proposed to allow the robot to transit between different interaction modes to suit the human. In [14], by following the barrier Lyapunov functions, a variable impedance controller was developed to deal with the physical constraints during pHRI, such as the joint and torque limits. In [19], a hierarchical compliance controller was proposed for redundant robots, to prioritize then deal with multiple tasks collaborating with the human. In [20], a variable admittance control strategy was proposed to deal with the varying human dynamics (resulting in the instability), by detecting the increasing oscillation then updating the admittance parameters.

In this paper, the adaptive impedance model is also constructed to describe the human motion intention. In particular, the human motion intention is extracted from the impedance model of the human limb, then it is estimated with adaptive NNs (ANNs). Based on the estimated human motion intention, a new intention-driven control scheme is proposed to drive the robot to track that intention under a desired variable impedance model. Instead of simply leading the human or following the human, the proposed controller allows the robot to continuously assess the human motion intention then progressively amplify/lower its assistance beforehand. The safety of the proposed pHRI system is guaranteed in both the hardware (i.e. the compliant actuator) and the software (i.e. the dynamic impedance). The stability of the closed-loop system and the convergence of the impedance error to zero are rigorously proved with Lyapunov methods, experimental results on a lower-limb exoskeleton robot are presented to...
evaluate the performance of the proposed controller.

II. PRELIMINARIES

Understanding the human motion intention is fundamental to robotic systems involving the interaction with humans. In this paper, the human motion intention is described by the model of the human limb [12], [13]

\[ D_h(q_h - \dot{q}_d) + K_h(q_h - q_d) = \tau_e, \]  

(1)

where \( q_h \in \mathbb{R}^n \) is the vector of the joint angles of human limb, \( n \) is the total number of degrees of freedom (DoFs), \( D_h, K_h \in \mathbb{R}^{n\times n} \) denote the parameters of damping and stiffness respectively which can be time-varying, \( \tau_e \in \mathbb{R}^n \) denotes the interaction torque, and \( q_d \in \mathbb{R}^n \) is the vector of the desired joint angles, which is treated as the human motion intention in this paper. Both the interaction torque \( \tau_e \) and the joint angles \( q_h \) can be measured with the sensors mounted on the human limb in the actual implementation. But the intention describes the underlying change in the human limb, which can not be directly measured with sensors.

This paper considers a wearable robotic system, where the human subject wears the robot for purposes of augmentation or rehabilitation. In such a system, the robot is usually driven by compliant actuators. One example is the series elastic actuator (SEA) [21], which consists of a piece of elastic steel connected between the executed object and the motor. Because of the elastic material connected to the motor, the compliant actuators have the attractive features of tolerance to impacts and the storage of energy, which is very suitable for applications involving pHRI.

The dynamic model of the robot and compliant actuator are given as [2], [22]:

\[ M(q)\ddot{q} + \frac{1}{2} M(q) + S(q, \dot{q})\dot{q} + g(q) = K(\theta - q) + \tau_e, \]  

(2)

\[ B\dot{\theta} + K(\theta - q) = u, \]  

(3)

where \( q \in \mathbb{R}^n \) is the vector of the joint angles of the robot, \( \theta \in \mathbb{R}^3 \) is the vector of the rotor shaft positions of the actuator. The first three terms on the left side of (2) denote the inertia effect, the centripetal and Coriolis torque, and the gravitational torque respectively. In (3), \( K \in \mathbb{R}^{n\times n} \) is the stiffness matrix which is diagonal and positive definite, \( B \in \mathbb{R}^{n\times n} \) is the inertia matrix of the actuator which is diagonal and constant, and \( u \in \mathbb{R}^n \) is the control input.

Some important properties of the dynamic model in (2) and (3) are listed as follows [23], [24]:

(i) The dynamic parameters \( M(\cdot), S(\cdot) \), and \( g(\cdot) \) are bounded;
(ii) The matrix \( M(\cdot) \) is symmetric and positive definite;
(iii) The matrix \( S(\cdot) \) is skew-symmetric;
(iv) The left side of (2) can be expressed in terms of a set of parameters (e.g. mass, inertial) \( \psi \in \mathbb{R}^{n \times n} \) as:

\[ M(q)\ddot{q} + \frac{1}{2} M(q) + S(q, \dot{q})\dot{q} + g(q) = Y_q(q, \dot{q}, \dot{q}, \ddot{q})\psi, \]  

(4)

where \( Y_q(\cdot) \in \mathbb{R}^{n\times n} \) is a known regressor matrix.

Note that the first \( \dot{q} \) in \( Y_q(\cdot) \) comes from the matrix \( S(q, \dot{q}) \), and the second \( \dot{q} \) in \( Y_q(\cdot) \) denotes the vector outside the brackets on the left side of equation (4).

In this paper, the exact knowledge of \( K \) and \( B \) in (3) is assumed to be known, which can be obtained from the data-sheet of the actuator. Then, the dynamic parameters of the robot (i.e. \( M(\cdot), S(\cdot), \) and \( g(\cdot) \)) are usually unknown, which will be updated with adaptation laws.

III. INTENTION-DRIVEN pHRI

In this section, the new intention-driven controller is proposed for pHRI to drive the robot to continuously adjust its impedance with the adaptation of the human motion intention. Such a feature can suit human behavior for better collaboration. The structure of the proposed controller is illustrated in Fig. 1.

![Fig. 1. The overall structure of the pHRI system. The intention estimator receives the information from the motion of the human limb (i.e. \( q_h \)) and the interaction force (i.e. \( \tau_e \)) then outputs the estimated desired joint angles (i.e. \( \dot{q}_d \)). The impedance controller receives the information about the human motion intention then adjusts the impedance parameters (i.e. \( M_d, C_d, K_d \)) through weighting function.](image)

A. Online Adaptation

Note that (1) can be expressed as

\[ Ay = \tau_e, \]  

(5)

where

\[ y \triangleq \begin{bmatrix} q_h - q_d \\ \dot{q}_h - \dot{q}_d \end{bmatrix} \in \mathbb{R}^{2n}, \]

\[ A \triangleq [D_h, K_h] \in \mathbb{R}^{n\times 2n}, \]  

(6)

where matrix \( A \) includes the information about parameters of the human limb. Those parameters are usually time-varying and not identical for different human subjects (e.g. different weight, age, gender). Hence, it is difficult to obtain their exact knowledge and the exact information about matrix \( A \).

From (5), it is obtained that

\[ y = A^+ \tau_e, \]  

(7)
where \( A^+ \) is the pseudo-inverse of \( A \).

In this paper, the technique of adaptive NNs [25] is used to approximate the signal \( y \) as

\[
y = \hat{W} \phi(q_h, q_b, \tau_e) + E,
\]

(8)

and \( \hat{W} \in \mathbb{R}^{2n \times n_w} \) denotes the estimated weight, \( E \in \mathbb{R}^{2n} \) is the vector of the approximation errors, and \( \phi(\cdot) \in \mathbb{R}^{n_w} \) is the vector of a series of activation functions, which receive the input of \( q_h, q_b, \tau_e \). In this paper, the activation function is specified as the Radial Basis Function (RBF). The use of ANNs requires neither the pre-training phase nor the structure information of the model, so it is applicable to human subjects with different and unknown dynamic parameters.

Then, the estimated desired joint angles can be retrieved from (8), with the measurement of \( q_h, q_b, \tau_e \). The above formulation explores both the current information of human limb (i.e. \( q_h \)) and also the intention reflected in the interaction torque (i.e. \( \tau_e \)), and hence it can predict the human’s future intention (i.e. \( \hat{q}_d \)) to guide the robot beforehand.

The update of the weights of NNs can be carried out by referring to the algorithm of gradient descent [13] as

\[
\hat{W}_j = -L_j \phi(\cdot) \tau_{ej},
\]

(9)

where \( \hat{W}_j \) is the \( j \)-th column of \( \hat{W} \), \( L_j \in \mathbb{R}^{n_w \times n_w} \) is a positive-definite matrix, \( \tau_{ej} \) is the \( j \)-th element of \( \tau_e \).

B. Task Planning

The control objective of the robot is specified as the variable impedance model as

\[
M_d(\ddot{q} - \ddot{\hat{q}}_d) + C_d(\dot{q} - \dot{\hat{q}}_d) + K_d(q - \hat{q}_d) = \tau_e/w(\cdot),
\]

(10)

driving the robot to follow the estimated human motion intention (i.e. \( \hat{q}_d \)) for assistance, where \( w(\cdot) \) is a weighting function, which is to be designed to vary the impedance during the interaction, and \( M_d, C_d, K_d \in \mathbb{R}^{n \times n} \) denote the desired inertia, the desired damping, and the desired stiffness matrices respectively, which are diagonal and constant.

The variable impedance model (10) can be rewritten as

\[
M_d(t)(\ddot{q} - \ddot{\hat{q}}_d) + C_d(t)(\dot{q} - \dot{\hat{q}}_d) + K_d(t)(q - \hat{q}_d) = \tau_e, \quad (11)
\]

where \( M_d(t) \triangleq w(\cdot)M_d, \quad C_d(t) \triangleq w(\cdot)C_d, \quad \text{and} \quad K_d(t) \triangleq w(\cdot)K_d \). That is, the impedance parameters increase as the weighting function is scaled up, and vice versa.

An example of the weighting function can be given as

\[
w(\cdot) \triangleq \frac{w(q, \hat{q}_d) = w_H - (w_H - w_L) \times \min[0, \min(0, h(q, \hat{q}_d))]^{N - (k^2 - 1)^N}}{(k^2 - 1)^N}, \quad (12)
\]

where \( w_H, w_L \) are positive constants representing the upper and lower bounds of \( w(\cdot) \) respectively (\( w_H > w_L \)), \( N \geq 4 \) is an even integer, and \( 0 < k < 1 \) is a constant, and \( h(\cdot) \) is the function of a region, which is specified as

\[
h(q, \hat{q}_d) = \frac{||q - \hat{q}_d||^2 - R^2}{2R},
\]

(13)

where \( R \) is a positive constant.

About the weighting function (12), \( w(\cdot) = w_H \) (maximum value) where \( h(\cdot) < 0 \), \( w(\cdot) = w_L \) (minimum value) where \( h(\cdot) > 0 \). Then, the robot impedance varies according to weighting function as

- When the robot motion matches the human motion intention, \( ||q - \hat{q}_d|| < R \), the output of the weighting function is large, such that the robot maintains a high impedance to amplify the assistance.
- When some conflicts arise between the human and the robot, \( ||q - \hat{q}_d|| > R \), the output of the weighting function becomes small, the robot becomes passive with a lower impedance, to alleviate the conflict then avoid potential injuries to the human.

The weighting function can also be extended to multiple levels as \( w(\cdot) = w_1 \times w_2 \), where \( w_1, w_2 \) can be constructed by following the similar development in (12).

Remark: The proposed variable impedance model is a unified formulation for wearable robots used in the applications of both the augmentation and the rehabilitation. For rehabilitation robots, the desired trajectory in (10) can be predefined by referring to the movement trajectory of a healthy human subject, instead of the estimated desired joint angle.

C. Interaction Control

Multiply both sides of (10) with \( M_d^{-1} \) and rewrite it as

\[
(\ddot{q} - \ddot{\hat{q}}_d) + M_d^{-1}C_d(\dot{q} - \dot{\hat{q}}_d) + M_d^{-1}K_d(q - \hat{q}_d) = -M_d^{-1}\tau_e/w(\cdot) = 0, \quad (14)
\]

Next, an impedance vector [26] is introduced as

\[
z = \ddot{q} - \ddot{q}_z = \ddot{q} - \ddot{\hat{q}}_d + \Lambda(\dot{q} - \dot{\hat{q}}_d) - \tau_i, \quad (15)
\]

where

\[
\dot{q}_z = \dot{q}_d - \Lambda(\dot{q} - \dot{\hat{q}}_d) + \tau_i, \quad (16)
\]

which is a reference vector, and

\[
\Lambda + \Gamma = M_d^{-1}C_d, \quad (17)
\]

\[
\Gamma\Lambda = M_d^{-1}K_d, \quad (18)
\]

\[
\tau_i + \Gamma\tau_i = M_d^{-1}\tau_e/w(\cdot), \quad (19)
\]

that is, \( \Lambda, \Gamma \in \mathbb{R}^{n \times n} \) are two positive-definite and diagonal matrices, and \( \tau_i \in \mathbb{R}^n \) is the low-pass filtered signal of \( M_d^{-1}\tau_e/w(\cdot) \).

By using (15)-(19), the left side of (14) can be expressed in terms of \( \dot{z} \) and \( z \) as

\[
(\ddot{z} - \ddot{\hat{q}}_d) + M_d^{-1}C_d(\dot{q} - \dot{\hat{q}}_d) + M_d^{-1}K_d(q - \hat{q}_d) = -M_d^{-1}\tau_e/w(\cdot) = \dot{z} + \Gamma z. \quad (20)
\]

Then, it can be shown that the convergence of \( z \to 0 \) leads to the realization of the variable impedance model (10) in the low-frequency range [27].

As the overall dynamic model described by (2) and (3) has the recursive structure, the development of the controller follows a backstepping approach [27], [28]. That is, a virtual desired position input is proposed to the convergence of \( z \to 0 \)
0 first, then a final control input (28) is proposed to drive the position of rotor shaft to converge to the virtual desired position input.

By using (15) and Property (iv) in Section II, equation (2) can be written as

\[ M(q) \ddot{z} + \left( \frac{1}{2} \dot{M}(q) + S(q, \dot{q}) \right) z + Y_q(q, \dot{q}, \dot{q}_z, \dot{q}_z) \psi_q + K q \]

\[ = K \theta_d + K \Delta \theta + \tau_e, \quad (21) \]

where \( \Delta \theta = \theta - \theta_d \), and \( \theta_d \) is the virtual desired position input for the robot.

Now, the virtual desired position input can be proposed as

\[ \theta_d = q - K^{-1} (\tau_e + K_z z - Y_q(q, \dot{q}, \dot{q}_z, \dot{q}_z) \dot{\psi}_q), \quad (22) \]

where \( K_z \in \mathbb{R}^{n \times n} \) is diagonal and positive-definite, and \( \dot{\psi}_q \) represents the estimate of \( \psi_q \), which is updated by

\[ \dot{\psi}_q = -L_q \dot{Y}_q^T(q, \dot{q}, \dot{q}_z, \dot{q}_z) z, \quad (23) \]

where \( L_q \in \mathbb{R}^{n \times n} \) is a diagonal and positive-definite matrix which regulates the convergence of estimated parameters.

Substituting (22) into (21) yields the following dynamic equation

\[ M(q) \ddot{z} + \left( \frac{1}{2} \dot{M}(q) + S(q, \dot{q}) + K_z z \right) z + Y_q(q, \dot{q}, \dot{q}_z, \dot{q}_z) \Delta \psi_q = K \Delta \theta, \quad (24) \]

where \( \Delta \psi_q = \psi_q - \dot{\psi}_q \).

Next, the control input for the actuator \( u \) is developed such that the actual position of the actuator \( \theta \) tracks the desired input \( \theta_d \) and hence \( \Delta \theta \to 0 \). First, a sliding vector is introduced for actuator as

\[ s = \theta - \dot{\theta}_s = \dot{\theta} - \dot{\theta}_s + \alpha (\theta - \theta_d) = \Delta \theta + \alpha \Delta \theta, \quad (25) \]

where \( \alpha \) is a positive constant, and \( \dot{\theta}_s \) is a reference vector which is defined as

\[ \dot{\theta}_s = \dot{\theta}_d - \alpha \Delta \theta. \quad (26) \]

Using the sliding vector \( s \), the dynamics of the subsystem (3) is expressed as

\[ B \dot{s} + K (\theta - q) + B \dot{\theta}_s = u. \quad (27) \]

Now, the control input of the actuator can be proposed as

\[ u = K (\theta - q) - K_s s - K_\theta \Delta \theta + B \dot{\theta}_s \quad \text{(28)} \]

where \( K_s, K_\theta \in \mathbb{R}^{n \times n} \) are positive-definite matrices.

Substituting (28) into (27), the closed-loop equation of the wearable robot is obtained as

\[ B \dot{s} + K_s s + K_\theta \Delta \theta = 0. \quad (29) \]

We can now propose the following theorem.

**Theorem:** The variable impedance control scheme described by (22), (23), and (28) for the compliantly actuated robot described by (2) and (3) ensures the convergence of the impedance vector to zero, if the control parameters are chosen such that

\[ \alpha^2 \lambda_{\min}[K_z K_\theta] \geq \frac{1}{4} \lambda_{\max}[K^2]. \quad (30) \]

where \( \lambda_{\min}[] \) and \( \lambda_{\max}[] \) denote the minimum and maximum eigenvalues respectively.

**Proof:** To prove the stability, a Lyapunov-like candidate is proposed as

\[ V = \frac{1}{2} z^T M(q) z + \frac{1}{2} \Delta \psi_q^T L_q^{-1} \Delta \psi_q + \frac{1}{2} s^T B s + \alpha \Delta \theta^T K_\theta \Delta \theta. \quad (31) \]

Differentiating (31) with respect to time, we have:

\[ \dot{V} = z^T M(q) \ddot{z} + \frac{1}{2} z^T M(q) z - \Delta \psi_q^T L_q^{-1} \dot{\psi}_q \]

\[ + s^T B \dot{s} + 2 \alpha \Delta \theta^T K_\theta \dot{\Delta} \theta. \quad (32) \]

Substituting (23), (24), and (29) into (32) and using Property (iii) in Section II, we have:

\[ \dot{V} = -z^T [ (S(q, \dot{q}) + K_z) z - K \Delta \theta ] \]

\[ + Y_q(q, \dot{q}, \dot{q}_z, \dot{q}_z) \Delta \psi_q - \Delta \psi_q^T L_q^{-1} \psi_q + 2 \alpha \Delta \theta^T K_\theta \Delta \theta - s^T B \dot{s} = -z^T K_z z + z^T K \Delta \theta \]

\[ + 2 \alpha \Delta \theta^T K_\theta \Delta \theta - s^T K_\theta \dot{s}. \quad (33) \]

Note that \( s = \Delta \theta + \alpha \Delta \theta \), (33) can be written as:

\[ \dot{V} = -\Delta \theta^T K_\theta \Delta \theta \]

\[ - [z^T \Delta \theta]^T \left[ \begin{array}{cc} K_z & -\frac{1}{2} K \\ -\frac{1}{2} K & \alpha^2 K_\theta \end{array} \right] [z^T \Delta \theta]^T. \quad (34) \]

If the condition (30) is satisfied, we have \( V > 0 \) and \( \dot{V} \leq 0 \). Therefore, \( V \) is bounded. The boundedness of \( V \) ensures the boundedness of \( z \), \( \Delta \psi_q \), \( s \), and \( \Delta \theta \). The boundedness of \( s \) and \( \Delta \theta \) ensures the boundedness of \( \dot{s} \), and thus \( \Delta \theta \) is uniformly continuous. The boundedness of \( z \) ensures the boundedness of \( q - q_d \) and \( q - q \) from (15). Since both \( q_d \) and \( q_d \) are bounded, \( q_z \), and \( q_d \) are also bounded. Since \( q_z \), \( q_d \), \( \Delta \psi_q \), \( \Delta \theta \), and \( z_q \) are all bounded, \( z \) is bounded from (24). Therefore, \( z \) is also uniformly continuous. From (34), \( z \) and \( \Delta \theta \) are bounded in \( L^2 \). Then it follows [23] that \( z, \Delta \theta \to 0 \). Hence, the desired variable impedance model is realized.

**IV. Experiment**

The proposed intention-driven variable impedance controller has been implemented in a lower-limb exoskeleton robot as shown in Fig. 2. The motion of the exoskeleton is controlled by the microchips on the robot, and the overall robotic system consisted of the sensing module (i.e., encoders, IMUs, force gauges, EMG wireless transducer), the control module, and the actuators. In particular, the SEAs are deployed, where the stiffness is specified as 635 N/m, and the rotation is measured with the encoders (2048 lines) at both ends of the spring. The IMU sensors (JY901) and the force gauges (Sichiray) are mounted on the human body to measure his/her motion and the interaction torque respectively. The EMG wireless transducers are mounted on different locations of the human leg respectively (see Fig. 2), to collect the feedback from the human when wearing the exoskeleton and hence assess the functionality of the control.
The proposed control algorithm receives the sensory feedback from the encoders, the IMUs, and the force gauge, then it generates the corresponding pulse-width modulation (PWM) signal, which is transferred to the control module to drive the joints of the exoskeleton robot via the SEAs.

In the first experiment, comparative studies were carried out to illustrate the effectiveness of the proposed variable impedance model. In particular, the estimated human intent was replaced with a predefined trajectory in the desired impedance model (8) as \( q_r = -0.3 + 0.3 \sin(0.2 + \pi t) \) rad, and other impedance parameters were set as: \( M_d = 1, C_d = 15, K_d = 13 \). Next, the control parameters in (28), (22), and (23) were set as: \( K_z = 25, \alpha = 15, K_s = 11, \zeta = 18, L_q = 0.1 \). Then, the weighting functions were set to specify two different impedance models respectively, that is, the variable impedance model \((w_L = 1, w_H = 10, \kappa = 0.6)\), and the fixed impedance model \((w(\cdot) \equiv 10)\). Both impedance models were implemented in the robotic exoskeleton hung on a shelf, for the sake of a better comparison. During the experiment, the human subject wore the developed exoskeleton and actively held the robot several times, and the results were seen in Fig. 3(a).

In Fig. 3(a), the weighting function varied according to the change of the offset \( q_h - q_r \) (i.e. \( q - \hat{q}_d \) in equation (13)), leading to the variable impedance model, and the impedance error at the steady-state was around \([-0.01, 0.01]\). In Fig. 3(b), the weighting function remained constant and hence the impedance model was fixed, and the impedance error at the steady-state was around \([-0.01, 0.01]\). The root mean squares (RMS) of EMG data throughout the experiment were shown in Fig. 4(a), where the RMS of the variable impedance model was smaller than that of the fixed one, that is, the human subject was more conformable with the variable impedance model in general. This was mainly because the variable impedance model was able to relieve the conflicts during the physical interaction and hence suit the human subject in a more natural way.
better way.

In the second experiment, the functionality of the proposed control scheme was tested in the walking scenario. In particular, the knee joint of the exoskeleton on the right side was driven with the proposed controller, and that on the left side was de-activated for comparison. The human motion intention (i.e. $\hat{q}_a$) was estimated with the adaptive NNs, and the proposed control scheme was implemented to assist the human subject, by incorporating the estimated intention into the variable impedance model. The parameters of the adaptive NNs and the control scheme remained the same, and the impedance errors and the weighting function values were shown in Fig 3(c), proving the successful realization of the variable impedance model. The results of the EMG data were shown in Fig. 4(b). That is, the proposed control scheme did function, as the RMS of EMG data on the right leg of the human (i.e. with assistance) was smaller than that on the left leg (i.e. without assistance). In addition, the experiment was performed again on the same leg of the human subject with and without assistance, the results were shown in Fig.4(c), which also implied the effectiveness of the proposed control scheme.

V. Conclusion

In this paper, a new solution has been presented for pHRI, by integrating the intent estimation, the task planning, the interaction control, and the theoretical justification under a unified framework. In particular, the human motion intention is explored and adapted, then the variable impedance controller is proposed to continuously adjust the assistance from the robot according to the change of the intention. Such a formulation helps the robot to predict the human’s behavior and hence act intelligently to suit the human. The stability of the closed-loop system has been rigorously proved with Lyapunov methods, and experimental results on the lower-limb exoskeleton robot have been reported to show the performance of the proposed controller. Future works will be devoted to the consideration of stochastic effects in the human motion intention.

References