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Motion Detection Enhanced Control of an Upper Limb Exoskeleton Robot for Rehabilitation Training*

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The paper studies the control design of an exoskeleton robot based on electromyography (EMG). An EMG-based motion detection method is proposed to trigger the rehabilitation assistance according to user intension. An adaptive control scheme that compensates for the exoskeleton's dynamics is employed, and it is able to provide assistance tailored to the human user, who is supposed to participate actively in the training process. Analysis of the experiment results verify the effectiveness of the control method developed in this paper.

Keywords: Human-like learning control; EMG motion detection; SVM-based classification.

1. Introduction

Most of the developed countries are facing various social problems caused by the aging population, and novel solutions are urgently required to address the decreased motor functionalities in the increasing population of elders as well as patients subject to motor injuries. In this context, many kinds of assistive exoskeleton robots have been developed to support rehabilitation training and/or daily life motions for physically weak people including disabled individuals^{1,2,3,4,5}. In recent years, the potential of robots to complement traditional one-on-one rehabilitation exercises with a human therapist and help restoring the motor function after stroke was demonstrated in several studies^{6,7,8,9,10,42,43,44}. We have developed a 5 joints upper limb exoskeleton robot for rehabilitation training purpose as reported in⁴⁵,

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and have performed preliminary studies on muscle electromyography (EMG) signals based control design on it.

This paper develops a motion detection based robot controller for the exoskeleton robot, motivated by three issues to be discussed below. The first issue is that subjects affected by neurological diseases, e.g., subacute poststroke patients, often cannot move their arm freely. A robot could be used to support these patients doing practice, however it is critical for the robot supports to follow accurately the human users' motion intention, such that the therapy's success could be achieved¹¹. It could be difficult to obtain physical signals reflecting his/her motion intention when a patient is not able to move the limb, while physiological signals such as EMG may be used to detect motion intention, because muscular contraction can be observed on EMG, which directly reflects the level of muscle activity in real-time¹³, and can be captured using surface electrodes. It is noted that EMG is highly variable, so that repeated movements of same task may not produce same muscle activation patterns. In addition, different subjects may use different muscles to achieve the same movement. Moreover, muscles often span over several joints, making it hard to distinguish the contribution of each muscle to different joint rotational movement. Following our previous work¹³, in this paper we employ a support vector machine (SVM) classifier to detect motion intention from the EMG signals, in order to solve the above mentioned problems.

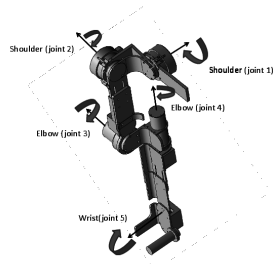
The second issue is about how to properly control the the exoskeleton robot to allow user to move freely without resistance. It is thus necessary to compensate for the exoskeleton's dynamics, especially gravity compensation. Using a precise dynamics compensation, low-feedback gains can be used along with a feedforward model to accurately follow a desired movement. Our home-built exoskeleton robot uses harmonic drive systems that provide backdrivable actuation and accurate positioning with negligible backlash. Modeling of harmonic drive systems has been extensively studied^{14,15}. However, consider the fact that torque sensors are usually directly mounted on the transmission components for force control task¹⁶, we incorporate the nonlinearities of harmonic drive systems into the dynamics of the exoskeleton robot, in addition to friction, kinematic error, and nonlinear stiffness behavior.

The third issue is that passive movement of the patient driven by the rehabilitation robot is insufficient to promote motor recovery. In contrast, active participation of the patient is required to ensure a successful therapy^{17,18}. Therefore, in order to promote learning, the trainee should be supported in a way that assistance is decreased when s/he performs well. Remarkably, this matches the characteristics of a model of human motor learning that minimizes both movement error and effort^{19,20}, which we have recently developed as an extended nonlinear adaptive robot controller²¹. Therefore, an idea to provide assistance as needed to promote maximal recovery consists of tuning force²³ and impedance assistance provided by the robot according to the adaptive controller of²⁴.

This paper describes the control of an arm exoskeleton based on these principles. Section 2 first describes the compact exoskeleton with five degrees-of-freedom (DOF) that we have developed with harmonic drives. The human-like adaptive controller to identify the exoskeleton's dynamics and tune its assistance is then described in Section 3. Section 4 presents the algorithm for EMG-based motion detection, and Section 5 the experimental results to validate the novel EMG control and adaptive dynamic compensation.

2. Development of Upper Limb Exoskeleton

Out human arm generally has seven DOFs: abduction/ adduction and flexion/extension of the shoulder, rotation of the upper arm, flexion/extension of the elbow, forearm rotation, also called pronation/supination the forearm, and radial/ulnar deviation and flexion/extension of the wrist. It is desirable that the developed exoskeleton is compatible with the natural arm motion and workspace of the operator. Our developed exoskeleton robot architecture is shown in Fig.1a, which demonstrates anthropomorphic features of human arm with properly selected five rotary DOF: 2 DOF in the shoulder, elbow flexion/extension, forearm rotation and wrist flexion/extension. The axis of rotation for the elbow joint is placed in the line between the two epicondyles. The axis of rotation for the wrist joint is located in the line between the capitate and lunate bones of the carpus, which allows ergonomic training of natural arm movements.



(a) Mechanical design of the exoskeleton robot.



(b) Final set up with a human subject

Fig. 1. Illustration of the upper limb exoskeleton with 5 DOFs: 2 DOFs on shoulder, flexion/extension of the elbow, pronation/supination of the forearm and wrist flexion/extension.

Maxon DC flat brushless motor EC45 was selected to satisfy the speed and torque requirements, together with a harmonic transmission drive (model SHD-17-100-2SH for joints 1 and 2, model SHD-14-100-2SH for joints 3 and 4, and CSF-32-50-2A-GR for joints 5). This configuration, based on flat DC motors and pancake transmissions, is able to provide a maximum torque of $8Nm$, nevertheless the max-

imum torque was electronically limited to $3Nm$ in order to guarantee the safety of the user. High resolution encoders (2048 pulse/cycle) and Hall effect sensor are used to measure the angle between the joints, providing a sufficiently large bandwidth to measure movements effectively.

Due to the use of a simple design and compact actuators, the total weight of the final upper arm exoskeleton is approximately 3.0 kg. High resolution encoders (2048 pulse/cycle) and Hall effect sensor are used to measure the angle between the joints, providing a sufficiently large bandwidth to measure movements effectively.

A protocol for testing the system was performed to evaluate the usability and the range of workspace allowed to a normal user. The system was used in the laboratory to perform a wide variety of manoeuvres in free mode, demonstrating correct operation of the system which does not affect the normal range of motion of the user.

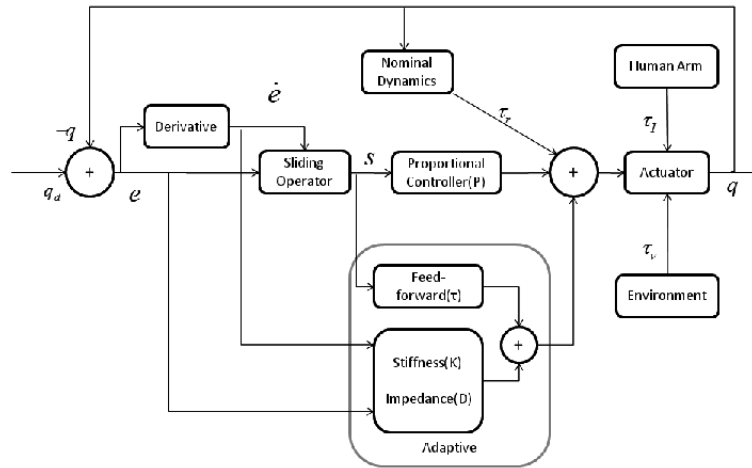


Fig. 2. Block diagram of controller.

3. Human-like Adaptive Control of Exoskeleton

3.1. Novel control principles

As it is impossible to model the human limb and the exoskeleton robot exactly, we propose to adapt feedforward force and impedance using a control scheme similar as observed in human motor learning²¹. The idea is that the robot will provide as much

force and impedance that is needed to guide the subject's movement successfully, but will tend to relax, so that a well performing subject would let the controller relax completely and thus perform the movement on his own effort.

To enable the subject start the movement when needed, thus enabling him/her natural control of the arm with the exoskeleton, EMG is used to detect motion intention. This is carried out using a classifier to detect between the two states of go or no go, and described in next section.

As in the rehabilitation training, subjects are usually supposed to repeat a certain movement a number of time. Therefore, in this paper we assume a periodic reference trajectory q_d :

$$q_d(t) = q_d(t - T) < \infty, \quad T > 0 \quad (1)$$

Consider an n DOF exoskeleton robot with dynamics

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + F(\dot{q}) + G(q) = \tau_\nu(t) + B(q)\tau_u + \tau_I(t) \quad (2)$$

where $q = [q_1, \dots, q_n]^T \in \mathbf{R}^n$ denote the generalized coordinates; $M(q) \in \mathbf{R}^{n \times n}$ is the symmetric bounded positive definite inertia matrix including the human arm and the robot; $C(q, \dot{q})\dot{q} \in \mathbf{R}^n$ denotes the centripetal and Coriolis torques for the human and robot; $F(\dot{q}) \in \mathbf{R}^n$ is the friction vector; $G(q) \in \mathbf{R}^n$ is the gravitational torque vector for the human and robot; $B(q) \in \mathbf{R}^{n \times m}$ is a full rank input transformation matrix and is assumed to be known because it is a function of fixed geometry of the system; $\tau_\nu(t)$ is bounded external noise with $\tau_\nu \leq \bar{\nu} < \infty$; τ_I is the interaction torque; and τ_u is the control input vector.

Let $e = q(t) - q_d(t)$ be the position error and $\dot{e} = \dot{q}(t) - \dot{q}_d(t)$ the velocity error, and define $s = \dot{e} + \kappa e$, then $\dot{q}_r = \dot{q}_d(t) - \Lambda e$ with the positive constant Λ , and $\dot{q} = \dot{q}_r + s$. We employ the controller depicted in Fig. 2 which is defined as follows:

$$B(q)\tau_u(t) = -\tau(t) - K(t)e(t) - D(t)\dot{e}(t) - P(t)s(t) + \tau_r(t) \quad (3)$$

where $-\tau(t)$ denotes the learned feedforward and $-K(t)e(t) - D(t)\dot{e}(t)$ represents the feedback which depends on stiffness $K(t)$ and damping $D(t)$ learned from environment interaction. All signals in the controller (3) are initialized with zeros, $-P(t)s(t)$ is the proportional control term, and $P(t)$ is symmetric positive-definite with minimal eigenvalues

$$\lambda_{min}(P(t)) \geq \lambda_P > 0 \quad (4)$$

that provides stable motion control. To compensate for the robot and arm dynamics and bounded noise, define

$$\tau_r(t) = M(q)\ddot{q}_r + C(q, \dot{q})\dot{q}_r + F(\dot{q}) + G(q) \quad (5)$$

In the above equation, $M(q)$, $C(q, \dot{q})$, $F(\dot{q})$ and $G(q)$ are functions of physical parameters like links masses, links lengths, moments of inertial and so on. The precise values of these parameters need to be acquired such that we can implement (5) in the control. In this paper, the inertia parameters are identified during motion. The

details of the robot link inertia and joint motor inertia and gravity parameters are listed in Table. 1.

Table 1. Inertia and Gravity Parameters

<i>joint/link</i>	M_i [kg/mm ²]	M_{link-i} [kg/mm ²]	m_i [kg]	l_i [mm]	l_{ci} [mm]
1	13.5	336	0.731	100	71.9
2	13.5	3807	0.701	250	193.0
3	3.5	972	0.670	40	27.9
4	4.8	60	0.120	230	158.0
5	3.5	122	0.427	30	27.8

Friction $F(\dot{q})$ in (5) is modelled as in ²⁷ with a Stribeck term and identified as follows: Torque is measured with velocity in all joints from 0.02 rad/s to 0.1 rad/s in intervals of 0.02 rad/s, and to 0.4 rad/s in intervals of 0.1 rad/s. 5 trials for each positive and negative directions of each velocity yield (using a least-square minimisation) the Stribeck curve

$$F(\dot{q}) = F_O \text{sgn}(\dot{q}) + F_V \dot{q} + F_S (1 - e^{-\frac{\dot{q}}{V_C}}) \quad (6)$$

where F_O , F_V , F_S and V_C are the coefficients of Stribeck curve (refer to Table 2 for the identified values). As motors in joints 1 and 2 are identical, parameters of joint 2 motor are simply set equal to the estimated parameters of joint 1), and \dot{q} is the joint velocity of the joint. On the other hand, the feedforward torque $\tau(t)$ in (3) to move the patient can be adapted through ²¹

$$\begin{aligned} \delta\tau(t) &= \tau(t) - \tau(t - T) = Q_\tau s \\ \tau(t) &= 0_{[n,1]}, \quad t \in [0, T) \end{aligned} \quad (7)$$

Table 2. coefficients of Stribeck Curve

joint [+]	F_O	F_V	F_S	V_C
1& 2	0.2512	-2.1214	2.2157	0.9661
3	0.1576	0.1290	0.0488	0.1147
4	0.0477	0.1818	0.0990	1.7047
5	0.0287	0.0389	0.0091	0.0181
joint [-]	F_O	F_V	F_S	V_C
1&2	0.2366	0.0658	-0.3855	-0.2791
3	0.1573	0.1360	-0.0413	-0.0721
4	0.0359	0.0177	-0.0262	-0.2492
5	0.0347	0.0362	-0.0066	-0.0361

where Q_τ is a symmetric positive-definite constant matrix. The stiffness and damping matrices are also adapted through ²¹

$$\delta K(t) = Q_K s(t) e^T(t), \quad \delta D(t) = Q_D s(t) \dot{e}^T(t) \quad (8)$$

where $K(t) = 0_{[n,n]}$ and $D(t) = 0_{[n,n]}$, $t \in [0, T)$, where Q_K and Q_D are symmetric positive-definite constant matrices. The stability and convergence of the above controller defined in (3), (5), (8) and (8) can be established as below. A Lyapunov function candidate as follows can be employed to analyze the stability

$$V = \frac{1}{2} s^T(t) M(q) s(t) \quad (9)$$

Consider the smooth interaction force can be linearized along the reference trajectories below:

$$\tau_I(t) = \tau_{I0} + K_I(t)e + D_I(t)\dot{e} \quad (10)$$

and follow a similar procedure as that proposed in ²¹, we can obtain

$$\begin{aligned} \dot{V}(t) &\leq -s^T Q_t s - s^T Q_k s e^T e - s^T Q_D s e^T e - s^T P s \\ &\leq 0 \end{aligned} \quad (11)$$

thus s converges to 0 as $t \rightarrow \infty$.

4. EMG based motion detection

4.1. Data Collection

Before collection, the skin of the upper limb is cleaned with 70% alcohol swab to remove any oil or dust from the skin surface. The EMG signal amplifier used is provided by CNNATION company, Shanghai, China. Seven channels of EMG signals are collected from the biceps brachii, triceps longus, pronator teres, extensor carpi ulnaris, extensor carpi ulnaris, flexor digitorum superficialis and abductor pollicis longus, when a certain subject undergoing seven distinct limb motions: elbow flexion, elbow extension, supination, pronation, wrist flexion, wrist extension, and rest. The signals are sampled at 1 kHz and are band-pass filtered between 10-500 Hz using a fourth order Butterworth filter, after which a notch filter is used to attenuate the power line frequency at 50 Hz.

Within each trial, the subject are asked to repeat a single motion nine times, with a duration of 7s each time and a 3s rest in between motions. The data collected from the first six times are used as training data and the data from the last three times are used as test data. To analyze the data collected, the data is first segmented with each segment consisting of data collection in 256ms following the same techniques in ²⁵, and there are 128ms overlap for training data and 32ms overlap for testing data. The data processing time is less than 20ms and therefore, in this work, real-time constraints enforce a time delay of less than 300 ms between the onset of muscle contraction made by a participant and a corresponding motion in the controlled device ²⁶. It is noted that generally a delay that is less than 300 ms is acceptable for myoelectric control ²⁵, as this delay would not be perceivable by human subjects.

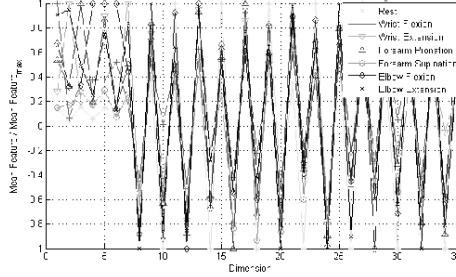


Fig. 3. Mean Feature of each dimension, where y label is $MeanFeature/MeanFeature_{Max}$, $MeanFeature_{Max}$ is the maximum value of the feature of the dimension in 7 motions.

4.2. Data Processing

As mentioned above, the motion intention detection task is to detect 7 states, namely, rest, wrist flexion, wrist extension, forearm pronation, forearm supination, elbow flexion and elbow extension. To achieve this goal, data will be processed in two main phases including feature extraction and classification. In addition, there are also pre-processing (e.g. amplification, filtering) and post-processing (e.g. smoothing). Five features are extracted from each 256 ms segment of EMG signal measure from every muscle, namely, (i) root mean square, (ii) mean absolute value, (iii) integrated absolute value, (iv) zero crossings, and (v) slope sign changes. All the features from seven muscles are combined into a 35×1 feature vector. The feature vectors of each state are calculated, and the mean values of these features are shown in Fig. 3.

The Support Vector Machine (SVM) method was used to classify EMG signals, which is a kernel-based approach that has recently been successfully applied to EMG classification applications³². The basic idea of SVM is to map the data to a higher dimensional feature space \mathcal{H} via a nonlinear mapping ϕ , and then carry out a linear regression in this space. Given a training set of l samples $(x_1, y_1), \dots, (x_l, y_l) \in \mathbb{R}^n \times \mathbb{R}$, we introduce a nonlinear mapping $\phi(\cdot) : \mathbb{R}^n \rightarrow \mathcal{H} \in \mathbb{R}^h$ which maps the training samples to a new data set $(\phi_1(x), y_1), \dots, (\phi_l(x), y_l)$. In ϵ -insensitive Support Vector Regression, the goal is to estimate the following function

$$\hat{f}(x) = \langle w, \phi(x) \rangle + b; \quad \omega \in \mathbb{R}^h, \quad b \in \mathbb{R} \quad (12)$$

where w and b are the coefficients, which are estimated by the risk function

$$R = \min_{w, b, \mathcal{E}} \left\{ \frac{1}{2} |w|^2 + \frac{c}{2} \sum_{i=1}^l \mathcal{E}_i^2 \right\}, \quad s.t. \quad y_i - \hat{f}(x_i) = \mathcal{E}_i \quad (13)$$

where l is the number of the training samples and the constant $c > 0$ measure the trade-off between complexity and losses.

We construct a Lagrangian to solve the optimization problem of equation below:

$$\begin{aligned} \max_a \min_{w,b} \left\{ L = \frac{1}{2} w^T w + \frac{1}{2} c \sum_{i=1}^l \mathcal{E}_i^2 \right. \\ \left. - \sum_{i=1}^l a_i \{ y_i - [w^T \phi(x_i) + b] - \mathcal{E}_i \} \right\} \end{aligned} \quad (14)$$

According to Karush-Kuhn-Tucker optimization condition, we can seek the optimal solution and transform this optimization problem into a matrix equation:

$$\begin{aligned} \begin{bmatrix} 0 & 1 & \dots & 1 \\ 1 & K(x_1, x_1) + \frac{1}{c} & \dots & K(x_1, x_l) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_l, x_1) & \dots & K(x_l, x_l) + \frac{1}{c} \end{bmatrix} \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_l \end{bmatrix} \\ = [0 \ y_1 \ \dots \ y_l]^T \end{aligned}$$

where $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$, $i, j = 1, \dots, l$, it is a kernel function, which satisfies the Mercer's theorem. In this paper, we select the polynomial kernel as follows:

$$K(x_i, x_j) = (r \times x_i \cdot x_j^T + c)^d; \quad (15)$$

where r , c and d are the three parameters to be adjusted.

4.3. Trajectory Generator

Since the outputs of SVM classifier are discrete motion, while the desired motion of exoskeleton needs amplitude and placement to generate the desired trajectory. We choose the desired joint trajectory as $q_d = A(1 - \cos(\pi t))$, where A is the user specified amplitude which is carefully predefined based on the joint position limit of the subject. For example, if the SVM classifier gives the result of elbow flexion, then elbow link moves from 0 to A rad along the sinusoidal curve. When the link reaches A rad, the elbow motor waits for elbow extension result from SVM classifier.

5. Experimental Results

For the assistive exercise, the exoskeleton robot assists the motion of the subject's arm to track a desired trajectory generated by detecting the subject's intension. By using EMG signals, the proposed control system could detect the subject's motion intension even though the subject is not able to move well. The desired trajectory generated by using user's motion tension is then sent to the controller, which enables the robot to s the subject's movement.

5.1. EMG recognition

In order to find the best parameters of the polynomial kernel of the SVM, we set different parameters and obtain the corresponding recognition accuracy as shown

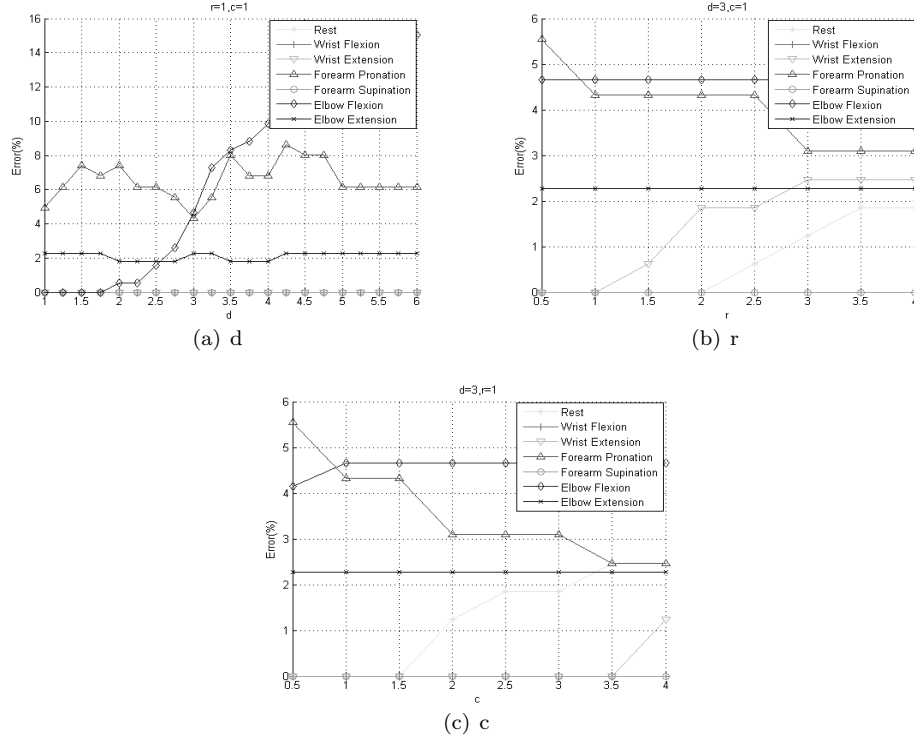


Fig. 4. Parameters adjustment

in Fig. 4. Firstly, we keep the other parameters as constants and only adjust d , (See Fig. 4(a)). Considering the trend of the Fig. 4(a), we choose $d = 3.0$, and then we compare different values of r . Finally, we select the default value $r = 1.0$ and $c = 2.0$ in Fig. 4(b).

In the experiment, as mentioned in Subsection 4.1, within each round, the EMG signals with length of 7 seconds for each motion are collected. Thus, repeated 9 times totally. The signals from the first 6 times are used as training data, and the rest 3 as the testing data. Therefore, for each motion, we have the signals with total length of 42 seconds as training data. For each motion, the length of the signals of the testing set is 21 seconds. With the steps of 32ms, 672 pieces of signals for each motions are tested to verify the proposed motion detector. The accuracy of recognition of each motion is shown in Table. 3. The proposed classifier can serve high accuracy.

Table 3. The recognition accuracy

States	Accuracy(%)
Rest	98.8
Wrist flexion	100
Wrist extension	100
Forearm pronation	96.9
Forearm supination	100
Elbow flexion	95.3
Elbow extension	97.7

5.2. Trajectory Control from EMG Signal

EMG recognition results give estimated human arm motion modes, and decide the joint No. and its direction, for simplification we assume the desired motion amplitude as 0.314 rad for the joint limit, and choose the desired trajectory as $q_d = 0.314(1 - \cos(\pi t))$, $t \in [0, 20]$. In the experiments with the human wearing the robot, we assume that the center of human limb mass coincides with the center of robot link mass with 0.7kg forearm and 0.65kg upperarm as the parameters of subject. The initial position of both shoulder joint is vertical to the horizontal plane, and elbow with 0.26 rad flexion. The initial positions of elbow rotating and wrist are with palm down, $\kappa = 2$, and the parameters of controller are listed in Table. 4.

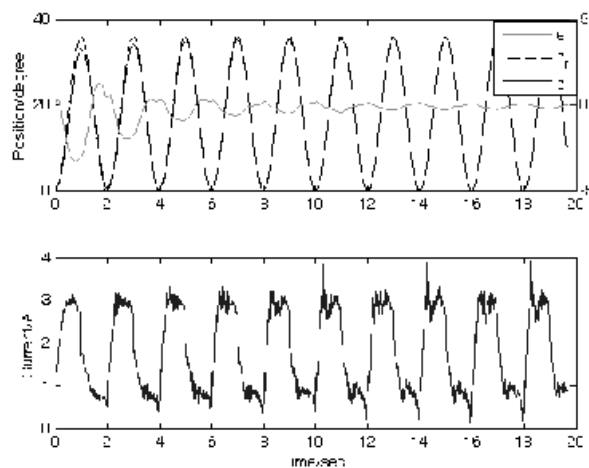
Table 4. Parameters of each joint controller

joint	P	Q_τ	Q_K	Q_D
1	0.18	1.5	1	0.7
2	0.18	1.5	1	0.7
3	0.035	0.5	0.3	0.3
4	0.02	0.3	0.2	0.2
5	0.02	0.3	0.2	0.2

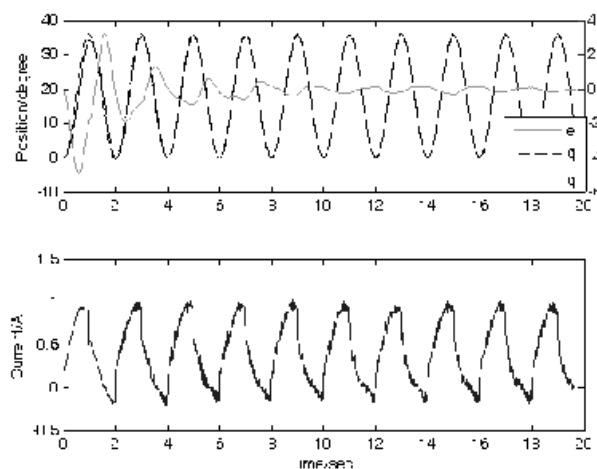
Fig. 5 shows the experiment results for one representative joint of the shoulder (joint 1 in Fig.1a) and one from the elbow joint (joint 3 in Fig.1a). The shoulder joint parameters are learned quickly and the control is stable during the experiment. The elbow joint exhibits good performance and the tracking error converges quickly.

6. Discussion

This paper developed a new control framework for the physical training of arm movements with a robot. It is critical that the robot motion guidance and assistance be generated corresponding to motion intention, in particular to detect when a



(a) Performance of shoulder flexion



(b) Performance of elbow flexion

Fig. 5. Learning control tracking error and motor current

subject wants to move, and also to detect motion intention in subjects unable to move by themselves, but still possessing residual muscle activity. Our system based on support vector machine could detect one-joint motion intention (as is probably sufficient for good robot-assisted physical therapy³⁸). While machine learning algorithms were used extensively to model joint torque^{39,40} or classify postures⁴¹ using EMG signals, this is, to our knowledge, the first attempt to detect motion based on EMG.

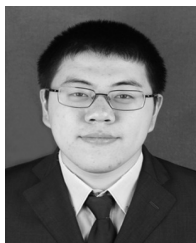
This EMG-based motion detection algorithm was used to control a dedicated compact arm exoskeleton. This paper further developed adaptation of torque and impedance to i) compensate for the exoskeleton's dynamics, and ii) assist motion as is needed to complete the training task successfully while promoting pro-active motor control. While a complete demonstration of this algorithm will require its testing on patients with motor impairments, tests demonstrated the capacity of this new adaptive controller compensate for the exoskeleton's dynamics and help a human subject perform accurate arm movements.

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