2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)
July 6-11, 2014, Beijing, China

Active Interaction Control of a Rehabilitation Robot Based on Motion Recognition and Adaptive Impedance Control

Wei Meng, Yilin Zhu, Zude Zhou, Kun Chen, Qingsong Ai
School of Information Engineering, Wuhan University of Technology
Key Laboratory of Fiber Optic Sensing Technology and Information Processing, Ministry of Education
Wuhan, Hubei 430070, China
weimeng@whut.edu.cn

***Abstract*—Although electromyography (EMG) signals and interaction force have been widely used in patient cooperative or interactive training, the conventional EMG based control usually breaks the process into a patient-driven phase and a separate passive phase, which is not desirable. In this research, an active interaction controller based on motion recognition and adaptive impedance control is proposed and implemented on a six-DOFs parallel robot for lower limb rehabilitation. The root mean square (RMS) features of EMG signals integrating with the support vector machine (SVM) classifier were used to online predict the lower limb intention in advance and to trigger the robot assistance. The impedance control strategy was adopted to directly influence the robot assistance velocity and allow the exercise to follow a physiological trajectory. Moreover, an adaptive scheme learned the muscle activity level in real time and adapted the robot impedance in accordance with patient's voluntary participation efforts. Experimental results on several healthy subjects demonstrated that the lower limb motion intention can be precisely predicted in advance, and the robot assistance mode was also adjustable based on human-robot interaction and muscle activity level of subjects. Comparing with the conventional EMG-triggered assistance methods, such a strategy can increase patient's motivation because the subject's movement intention, active efforts as well as the muscle activity level changes can be directly reflected in the trajectory pattern and the robot assistance speeds.**

Keywords*—rehabilitation robot; EMG; motion recognition; impedance control; active interaction control

I. INTRODUCTION

It is evident that there is a strong trend that our society is fast-aging than expected. According to the official statistical data from the United Nations, the proportion of the world's population over 60 years old will be doubled from 11% to 22% between 2000 and 2050. Meanwhile, limb fractures commonly occur because of sports injuries, car accidents and other accidental injuries. With the tendency of aging society, there is a considerable increase in the needs of health care and rehabilitation, especially among old and disabled people [1]. The rehabilitation training with robot assistance plays a significant role in recovering the limb motor functions. Moreover, evaluation for patient's recovery condition and an active interaction control strategy that provide appropriate assistance is essentially necessary during the rehabilitation[2]. A systematic review of methods and techniques for assistive strategies based on patient's participant performance had been summarized by Marchal-Crespo et al. [3].

This work was funded by the Fundamental Research Funds for the Central Universities (Grant no. 2013-YB-002).

Since the EMG signals contain much crucial information of the muscle activity, and can imply people's movement action 30~100ms in advance [4], they have been widely used in clinical diagnosis, rehabilitation, prosthetic control, and the human-robot interaction. In recent years, many methods have been proposed to extract useful information from EMG signals [5]. However, a majority of research was conducted on upper limbs [6]. For example, Kiguchi et al. proposed an EMG signals-based method to control an upper-limb robot according to the user's motion intention. In this situation, sixteen channels of EMG signals were used to estimate the upper-limb motion [7]. Krebs et al. described a performance-based progressive therapy using EMG to initiate the robot assistance [8]. In this research, the EMG signals in fourteen muscles of the upper limb were collected, and the robot was triggered when the one muscle's activity increased above a threshold. This EMG-triggered assistance encourages self initiated movement by patients, however, this approach may not receive satisfactory rehabilitation outcomes, because it breaks the movement into two separate phases, a active phase driven by patient, and a passive phase driven by robot, rather than providing a seamless assistance to subject [9].

The potential problem with EMG-triggered assistance is that it does not consider the participation of patient's efforts. The patient's recovery level can be reflected by EMG, while the voluntary participation is related to the interaction force between patient and robot. Several control strategies have been developed to provide robotic assistance according to the patient's disability level and his/her voluntary participation. An interactive training strategy is mostly achieved by using impedance controller. An assist-as-needed gait training based on impedance control was developed in [10] to provide interactive robotic gait training. However, a fixed treadmill speed was applied during the whole experiments. Similarly, Duschau-Wicke et al. presented a path control strategy with a virtual wall to keep the patient's legs within a tunnel around the desired path, again, a constant treadmill speed was used throughout the experiments [11]. It is well known that the basis of adaptive impedance assistance is to modify the robot motion in a way that is desired by the patient, which is believed to be the most appropriate for rehabilitation. However, the issue of reference trajectory adaptation has some drawbacks, for example, the extent of the trajectory adaptation can not be well determined and the changes in trajectory may result in an un-physiological pattern. In order to tackle this problem, the robot assistance speed can be adjusted according to human-robot interaction. Duchaine et al. designed a variable impedance controller using the force to sense human intention, and this work also demonstrated why velocity control should be used in a robot rather than typical position control [12]. Since in this situation, the desired physiological trajectory can be strictly followed, and the velocity changes influenced by the patient can also be obtained. And it may provide better opportunity for the patient to actively contribute his muscular efforts during the training process as compared to trajectory based training.

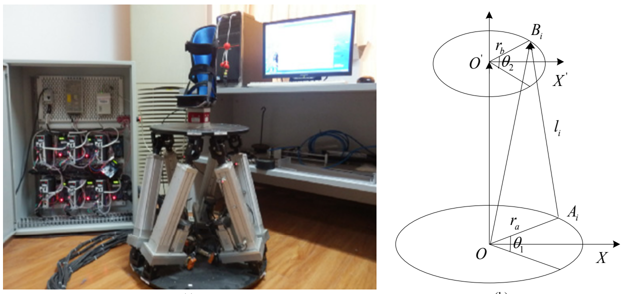
In this paper, an active interaction control strategy based on motion recognition and adaptive impedance controller is proposed and implemented on a six-DOF parallel robot for lower limb rehabilitation. A simple but effective recognition controller based on RMS features and SVM classifier is established to predict lower limb motion intention in advance. In order to increase patient's motivations during the exercise and keep the path physiological, an impedance controller is designed to make the robot speeds adaptable to patient's efforts. Furthermore, an adaptive scheme is developed for providing assist-as-needed robotic assistance. The controller takes into account the patient's muscle activity level and human-robot interaction to adapt robot compliance and the assistance speed accordingly. The proposed strategy allows patients to determine the trajectory pattern by recognizing EMG signals and influence the speed of their leg movements along a physiological path during the rehabilitation.

II. MATERIALS AND METHODS

A. 6-DOF Parallel Robot for Lower Limb Rehabilitation

Recently, parallel robots have drawn a lot of interests in the robotic community due to their superiority over the classical serial structures in terms of stiffness, accuracy, and high payloads. It has been found that parallel robots are good candidates for lower limb rehabilitation [13]. The lower limb rehabilitation robot designed in this paper is also a parallel mechanism with six transitional and rotational DOFs. The platform shown in Fig. 1(a) was designed by the authors' research group for the purpose of investigating lower limb rehabilitation. Specifically, the system mainly included a PC, six motion controllers based on DSPs, and Panasonic servo drivers, as well as the platform. Linear position and velocity of each actuator were measured by photoelectric encoders. The robot controller was implemented on a PC. The device was interfaced to a PC through a CAN BUS interface, and six actuators of the robot were controlled simultaneously to achieve full degrees of freedom for lower extremities.

The geometric diagram of Stewart platform is shown in Fig. 1(b), where the radius of the upper platform is defined as r_b, and the angle is θ_2, likewise, the parameters of the fixed platform are defined as r_a and θ_1, respectively. The radius of the upper moving plate is 180 mm, and the radius of the fixed base plate is 270 mm. Several safety features were also incorporated in the robotic mechanism and control hardware. Mechanical limit switches were placed on each joint to avoid the robot to go beyond the physiological ranges of motion. And an emergency switch was wired such that a single push can stop the whole system, which was held by the person invigilating the training process.



(a) (b)

Fig. 1. (a) is the 6-DOF parallel robot for lower limb rehabilitation, (b) is its geometric diagram.

B. Motion Recognition

EMG is often used to control the power-assist robot according to the user's intention since it directly reflects the user's movement intention and his muscle activity level in real time. Nowadays, there seems sufficient works have been done on EMG triggered assistance for upper limbs [14]. However, the lower limb robots have not yet been widely applied to the clinical rehabilitation. The problem is that the requirement of the real-time control for the lower limb is different from that of the upper limb. The lower limb has more freedoms and the muscle structure is complicated, it is difficult to accurately estimate the intended motions from multichannel EMG patterns using a fixed classifier [15]. In recent years, a number of methods have been proposed to extract useful information from EMG. These studies tried to extract the features in time, frequency or time-frequency domains, such as using AR coefficients, wavelet transform coefficients, and spectrum coefficients as feature variables [5]. The existing methods tend to be complicated or require huge amount of samples, most of them for lower limb EMG signal are less than ideal. In order to extract the features from raw EMG signals of lower limbs, the RMS of the EMG signal is calculated and used as an input for the recognition controller in this paper. The RMS calculation is written as

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\upsilon_i^2} \tag{1}$$

where N is the number of the segments (N = 512) and υ_i is the voltage at ith sampling.

SVM has gained wide acceptance in pattern recognition fields recently. It has been shown that SVM is superior to other traditional learning machines such as BPN, since SVM is able to gain better generalization ability for unseen data [16]. In this study, a method based on RMS features of EMG is proposed in combination with the SVM classifier, which is quite effective for solving nonlinear problems and reducing the computation burden. The feature extraction and SVM classification rules in this practice can be implemented and thus appropriate for real-time robot control applications. The structural diagram of classifier applied in our work is shown in Fig. 2. More detailed descriptions of SVM in can be found in papers [17, 18]. The major advantage of the approach applied in this paper is that it can be utilized in real-time action recognition during movements of the lower limb and provide robot assistance accordingly.

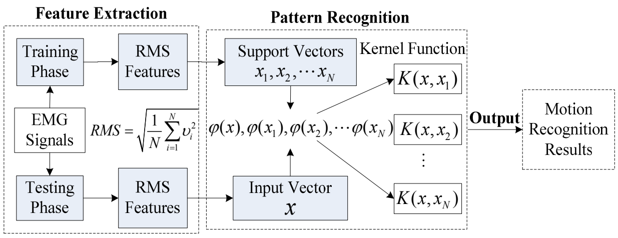


Fig. 2. Classification scheme for EMG-based motion recognition.

C. Adaptive Impedance Model

In order to provide a compliment environment after the robot being triggered, a flexible assistance can be provided by monitoring the interaction force between the user and the robot. Therefore, an admittance or position-based impedance controller is established. By measuring the interaction force applied by the user to the footplate, it is possible to compute reference position and speed required to render certain mass, stiffness, and damping features [19]. The impedance model of the mechanism with human interaction is expressed as:

$$M_d(\ddot{x} - \ddot{x}_d) + B_d(\dot{x} - \dot{x}_d) + K_d(x - x_d) = F_d - F_e \quad (2)$$

where M_d, B_d and K_d represent the desired inertia, damping, and stiffness matrices, x and x_d are the actual and the desired positions in the Cartesian space. F_e is the interaction force exerted upon the end-effector, and F_d is the desired force.

Classical impedance controller imposes fixed parameters on the patient and can not provide different impedance modes to different users. If the impedance setting is too stiff, patients feel passively moved; if it is too soft, patients might move in undesired patterns [11]. Therefore, the rehabilitation should be considered by monitoring the patient's muscle condition and updating the impedance parameters in real time. In this paper, the muscle activity level of patient is considered during the movement. The normalized RMS of EMG signals is used to evaluate the muscular activity ratio:

$$mar(t) = \sum_{i=1}^{n} \frac{RMS_i(t)}{init(RMS_i)} \quad (3)$$

where $RMS_i(t)$ presents the RMS value of channel i at time t, $init(RMS_i)$ is the initial value (in the training stage) of ith channel, and four channels of EMG signals are used (n=4).

In order to guarantee the training to be physiological, this controller works with a constant reference trajectory while adapts the velocities. Therefore, the damping coefficient of controller is the parameter to be adjusted. When there is little muscle activity ratio detected, the impedance (damping here) is set low in order to enforce the robot assistance speed easily changed to patient's efforts. The impedance is increased as soon as an increased muscle activity ratio is detected so that the patient can try his/her best to overcome the challenge. The reference trajectories are not modified and only the damping parameter B is adjusted as follows:

$$B(t) = B_0 + c \cdot sat(mar(t)) \quad (4)$$

where B_0 is initial viscous damping coefficient, c is the coefficient of the EMG effects, and $mar(t)$ is the muscle active ratio affected by the EMG signals. $sat(\,)$ is a saturation function to linear the regions between the maximum and the minimum saturation levels. Thus, the amount of damping parameters B is increased when the activity level of related lower-limb muscles is simultaneously increased.

In this active interaction training, voluntary participation of patients is required. The robot velocities are proportional to active interaction force, and the conversion formula can be presented by using impedance model [20]. The architecture for adaptive impedance controller is shown in Fig. 3. The lower loop is the impedance control with damping parameter, and the upper loop is a position/velocity controller. This architecture shows that more active interaction forces are required to achieve higher training velocities. Meanwhile, the damping coefficient can be changed for different training resistances according to the muscle activity level calculated from EMG signals. The higher the muscle ability is, the larger damping is, and more active force contributions are needed to reach the same exercise velocities.

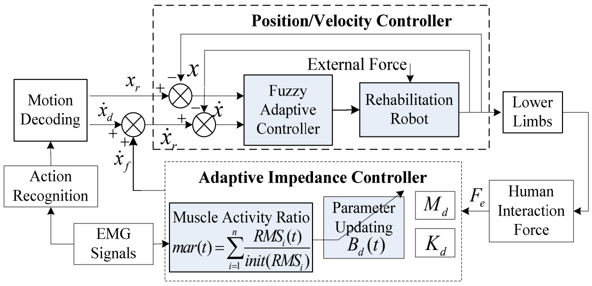


Fig. 3. Adaptive impedance control based on muscle activity evaluation.

D. Active Interaction Control

In this paper, we proposed a multi-DOF parallel robot for human lower-limb motion assistance, in which the EMG signals and active interaction force are integrated with the adaptive impedance controller to realize the effective motion assistance for the robot user. The active interaction control process in this study contains four steps as shown in Fig. 4: (1) EMG signals acquisition and preprocessing, including filtering and amplification; (2) limb intention prediction and motion decoding by the integration of RMS features of EMG and SVM classifier; (3) real-time updating of impedance parameters and joint velocity commands. A control law was proposed to relate the muscle activity ratio to the damping parameters in order to adjust the training speed in accordance with the human interaction force; (4) follow the predefined smooth trajectory based on inverse kinematics and fuzzy adaptive controller. The parallel rehabilitation robot has six DOFs, and a trajectory tracking approach based on a fuzzy controller was implemented as a position/velocity controller to guide the subject's limb on reference trajectories [1]. As the involvement of human control will necessarily promote patient activity during the exercise, such strategies can increase the patient's motivation because muscle activation changes and the interaction efforts will be directly reflected in the training speed and cause a consistent feeling of success.

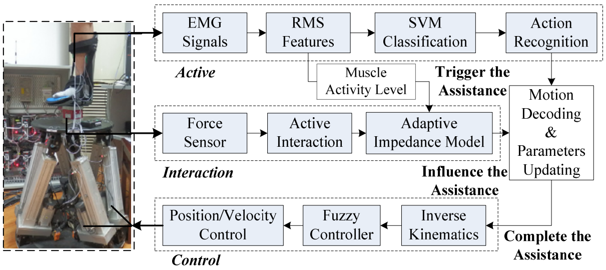


Fig. 4. The proposed active interaction controller for rehabilitation robot.

III. EXPERIMENTS AND RESULTS

A. *Experimental Protocol*

In order to evaluate the ability of the rehabilitation robot to provide interactive rehabilitation for lower limbs, the previously described robot and controller were implemented in preliminary experiments. The surface EMG signals were acquired by a portable EMG signals acquisition equipment (DataLOG MWX8, Biometrics Ltd. UK), as shown in Fig. 5(a). Moreover, a Futek force sensor was mounted between the moving platform and the footplate to sense the equivalent interaction force acting between human and robot.

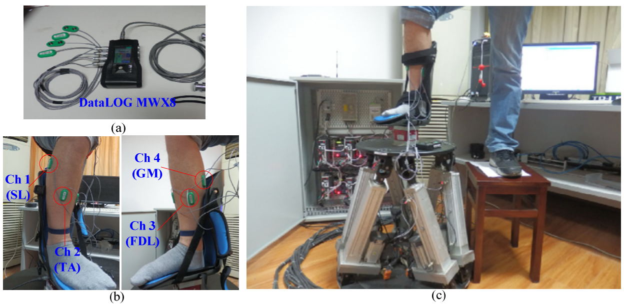


Fig. 5. (a) is the EMG acquisition equipment, (b) is the location of EMG electrodes, and (c) is the experimental setup.

The experiments were carried out with nine subjects aged range from 20 to 42, including both male and female subjects. Six motions including dorsiflexion, plantarflexion, inversion, aversion, adduction, and abduction [13], were implemented. Before the experiment, four pairs of electrodes were attached on each muscle. The subject's gastrocnemius medialis (GM), tibialis anterior (TA), flexor digitorum longus (FDL) and soleus (SL) muscles of the right leg were selected in this experiment. The location of electrodes is shown in Fig. 5(b). After a familiarization period, the subject stood on a chair with right foot constrained to the orthotics, as illustrated in Fig. 5(c). Considering the safety issue, the preliminary test was performed with healthy subjects. In the future, the robot will be changed to suit injured people and a height-adjustable chair will be equipped to comfort the participants.

Two forms of experiments were carried out to evaluate the effectiveness of the proposed control method. In the first experiment, all subjects performed the lower-limb motions with the passive assist of robot. This passive mode of the rehabilitation was investigated wherein the subject was asked not to exert any force and remain relaxed after the robot being triggered, and the robot was controlled to follow predefined trajectories. Then, experiments on active control based on real-time muscle activity evaluation and parameters updating were performed, where impedance parameters were adjusted to allow the patients to change the compliance by themselves. In the first stage, EMG signals were sampled, and recorded data were used as the training samples to modify the SVM classifier. In the second stage, the EMG signals with force feedback items were used to control the robot to follow the subject's specified motions and influence the movement in real-time. The subject was instructed to perform voluntary movements and participate in the training.

B. *Results*

The experimental results of three subjects were selected from nine participants to discuss the comparison between proposed and traditional methods. The experimental results of both EMG-triggered passive control and active interaction compliance control suggest that the robot can follow the subject's movement intention. The RMS features of captured EMG signals and SVM analysis method make it possible to predict human motion intention precisely. Fig. 6 shows the EMG signals and motion classification results of the selected subjects, where a satisfactory recognition accuracy (about 91.22%-95.44%) can be obtained.

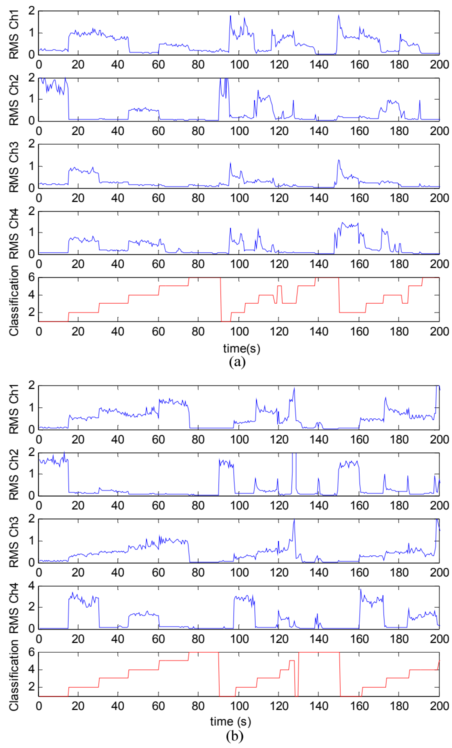


Fig. 6. RMS features extraction and motion recognition results. (a) is the results of subject 1 (S1) and (b) is the results of subject 2 (S2). Both figures (from top to bottom) show the RMS (mV) of SL, TA, FDL and GM muscles during the movement. And the classification results, in which the numbers from 1 to 6 present the six motions including dorsiflexion, plantarflexion, inversion, aversion, adduction, and abduction, respectively, showing that the recognition accuracy is satisfied.

For the second experiment, the effect of the adjustment of impedance parameters was evaluated. In order to encourage patient's participation in the training, robot compliance can be adjusted according to his/her muscle activity level. Fig 7(a) presents how patient's muscle activity ratio was evaluated during the exercise. And the experimental results in Fig. 7(b) show that the robot impedance parameters can be adjusted in accordance with the muscle activity ratio. When the muscle activity level is reduced, the impedance parameters will be properly adjusted to make the robot much "easier" to control. Afterwards, the subject was asked to take voluntary efforts that yielded a change of the motion velocity. The robot can not only follow subject's motion intention, but also influence the robot assistance speed based on interaction force and updating the impedance parameters according to muscle activity level, meeting the requirement of active and adaptive interaction control. The parameters of impedance controller can be updated based on the adaptation law mentioned above. The adjustment of the controller is simple and intuitive, since only a parameter is required and the effect of impedance can be interpreted as a compliant deviation from the desired speeds caused by patient's efforts.

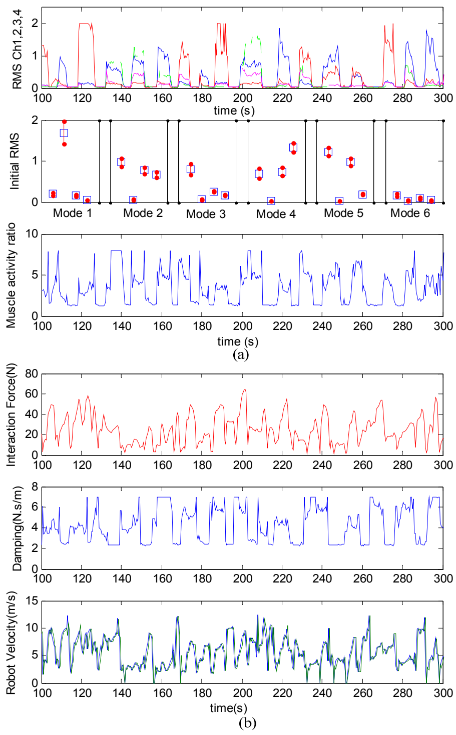


Fig. 7. (a) is the muscle activity evaluation results of S1 and (b) is the adaptive impedance control results of S1. From top to bottom of (a), the first one is the RMS of four channels (the blue, red, magenta, green line refer to channel 1, 2, 3, 4, respectively) during the exercise; the second one is the initial RMS value of four channels ($init(RMS_i)$, i=1,2,3,4, from left to right) for six motion modes in the training stage, since different motions activate different muscles, the average RMS and its deviation are shown for each channel in each mode,; the last one is the muscle of activity ratio evaluated by using (3). From top to bottom of (b), the first one is the resultant force of the active interaction in the x, y, z directions measured by force sensor; the second is the adaptive impedance parameter (damping here) which is shaped by the muscle activity ratio using (4); the last one is the average robot velocity in joint space (the blue line is the desired velocity and the green one is the actual one) determined by the interaction force and the damping coefficient.

Prior to the active interaction control mode, the subjects were trained in an EMG-triggered position control loop. Thus, comparisons can be done between the EMG-triggered control and active interaction control. Fig. 8(a, b) reports the amount of EMG signals required to perform the motion during the two trials. When the patient kept passive after activating the robot by EMG action recognition, the muscle efforts applied by the subject was at a lower level during the movement. Differently, in the second trial, the subject had to provide a certain effort in terms of muscle activity. It is noticed in Fig. 8 that the difference between the two modes is significant, especially when subject's muscle activity ratio is considered, and that the muscle efforts in active interaction impedance mode show an obvious increase in total EMG values. It is confirmed that the adaptive impedance controller can generate adaptive assistance speed in agreement with the change of the subject's muscle activity level. Therefore, the adaptive impedance controller is able to adjust the desired impedance between the robot and impaired limb to generate adaptive training speed in agreement with the limb's muscle strength. The advantage of the second trial is that they can voluntarily influence the robot speed and can feel the changes produced by their own contributions.

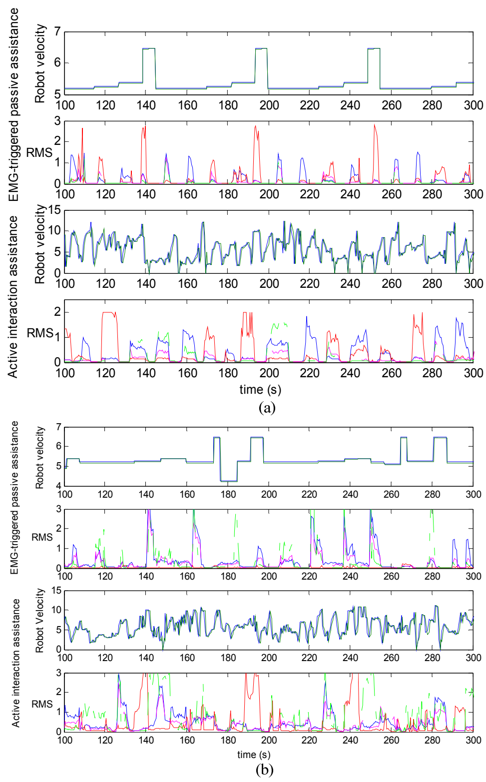


Fig. 8. Comparisons of the conventional EMG-triggered assistance and the active interaction control assistance. (a) is the results of S1 and (b) is the results of S3. From top to bottom of both (a) and (b), the top two figures are the robot velocity and RMS in EMG-triggered passive assistance; the bottom two figures are velocity and RMS recoded during the proposed active interaction assistance. It is illustrated that in conventional methods, the robot motion can not be influenced by subject after being triggered and the muscles are seldom active but just when triggering the robot. Whereas in the proposed method, the robot assistance speed can be adjusted according to external force and the muscle activity level, and thus the muscles are active at most of the time. This allows patient to contribute more efforts during the exercise and may increase the training effects.

IV. Discussion and Conclusion

Using impedance control instead of position control, the additional efforts by the patient can be reflected in the robot assistance pattern, which may increase his/her motivation. However, the modification of the reference trajectory may increase the risk that the subject and robot start to move out of physiological phase. Therefore, the robot assistance in this paper adjusted its speed based on patient's efforts, while keep the trajectories fixed. Furthermore, the impedance level can vary widely due to different levels of muscle activity ratio to match the patient's capabilities and recovery progress. In the proposed strategy, the patient's movement intention was first recognized using EMG signals. The RMS method is simple and effective to extract features from the raw EMG signals, and the results also demonstrate the effectiveness of the SVM classifier. It is suggested that the EMG signals recorded from selected muscles can be used to trigger the robot assistance. Then, impedance controller in accordance with patient's interactive efforts was applied to make the robot compliant; meanwhile, adaptive methods based on the muscle activity was used to adjust the impedance parameters and influence the robot assistance to individual contribution.

Experiments with healthy subjects were performed to evaluate if the adaptive impedance control scheme could modify the robotic assistance speed based on participation and muscle activity ratio of subject in the training process. The robot was operated in two different modes, namely, EMG-triggered mode and adaptive impedance control mode. In the first trial, all subjects were instructed to remain passive during the robot movement, and allowed robot to guide their legs based on intention recognition. In the second experiment, the subjects were asked to actively influence the robot assistance speed after triggering the robot. The experimental results demonstrated that the rehabilitation robot was able to move with the user's intention while the impedance can be updated. An increase in participation of subjects resulted in an increase of the robot speed and that an increase in muscle activity levels resulted in a decrease of the robot compliance. Comparing with the traditional EMG-triggered assistance, the proposed method not only activates the robot assistance when patient intends to move, but also changes the motion pattern in accordance with patient's efforts. Moreover, adaptation of robot impedance based on patient's muscle activity level directly responds to velocity changes, and this allows the limb move along a physiological trajectory.

In the future, in order to predict the patient's motion intention more precisely and make the controller more stable, the time-frequency domain features of EMG signals need to be introduced. In addition, six fixed movement patterns for healthy subjects were used during the experiments. However, these trajectories may not be suitable for the patients with different impairments. The adaptation of reference pattern and the construction force prediction based on lower limb EMG signals are also important research questions with regard to robot rehabilitation in future works.

Acknowledgment

This work was funded by the Fundamental Research Funds for the Central Universities (Grant no. 2013-YB-002).

References

[1] Z. Zhou, W. Meng, Q. Ai, Q. Liu, and X. Wu, "Practical velocity tracking control of a parallel robot based on fuzzy adaptive algorithm," Advances in Mechanical Engineering, vol. 2013, 2013.

[2] Y. Fan and Y. Yin, "Active and progressive exoskeleton rehabilitation using multi-source information fusion from sEMG and force & position- EPP," IEEE Trans. Biomedical Engineering, pp. 1-1, 2013.

[3] L. Marchal-Crespo and D. J. Reinkensmeyer, "Review of control strategies for robotic movement training after neurologic injury," Journal of Neuroengineering and Rehabilitation, vol. 6, Jun 2009.

[4] Y. H. Yin, Y. J. Fan, and L. D. Xu, "EMG and EPP-integrated human-machine interface between the paralyzed and rehabilitation exoskeleton," IEEE Trans. Information Technology in Biomedicine, vol. 16, pp. 542-549, Jul 2012.

[5] Q. S. Ai, Q. Liu, T. T. Yuan, and Y. Lu, "Gestures recognition based on wavelet and LLE," Australasian Physical & Engineering Sciences in Medicine, vol. 36, pp. 167-176, Jun 2013.

[6] H. H. Liu, "Exploring human hand capabilities into embedded multi-fingered object manipulation," IEEE Trans. Industrial Informatics, vol. 7, pp. 389-398, Aug 2011.

[7] K. Kiguchi and Y. Hayashi, "An EMG-based control for an upper-limb power-assist exoskeleton robot," IEEE Trans. Systems Man and Cybernetics Part B-Cybernetics, vol. 42, pp. 1064-1071, Aug 2012.

[8] H. I. Krebs, J. J. Palazzolo, L. Dipietro, B. T. Volpe, and N. Hogan, "Rehabilitation robotics: Performance-based progressive robot-assisted therapy," Autonomous Robots, vol. 15, pp. 7-20, Jul 2003.

[9] E. T. Wolbrecht, V. Chan, D. J. Reinkensmeyer, and J. E. Bobrow, "Optimizing compliant, model-based robotic assistance to promote neurorehabilitation," IEEE Trans. Neural Systems and Rehabilitation Engineering, vol. 16, pp. 286-297, Jun 2008.

[10] S. Hussain, S. Q. Xie, and P. K. Jamwal, "Adaptive impedance control of a robotic orthosis for gait rehabilitation," IEEE Trans. Cybernetics, vol. 43, pp. 1025-1034, Jun 2013.

[11] A. Duschau-Wicke, J. von Zitzewitz, A. Caprez, L. Luenenburger, and R. Riener, "Path control: A method for patient-cooperative robot-aided gait rehabilitation," IEEE Trans. Neural Systems and Rehabilitation Engineering, vol. 18, pp. 38-48, Feb 2010.

[12] V. Duchaine and C. M. Gosselin, "General model of human-robot cooperation using a novel velocity based variable impedance control," in EuroHaptics Conf. Symp. Haptic Interfaces for Virtual Environment and Teleoperator Systems, pp. 446-451, 2007.

[13] P. K. Jamwal, S. Q. Xie, S. Hussain, and J. G. Parsons, "An adaptive wearable parallel robot for the treatment of ankle injuries," IEEE/ASME Trans. Mechatronics, vol. PP, pp. 1-12, 2012.

[14] K. Kiguchi, T. Tanaka, and T. Fukuda, "Neuro-fuzzy control of a robotic exoskeleton with EMG signals," IEEE Trans. Fuzzy Systems, vol. 12, pp. 481-490, Aug 2004.

[15] Z. J. Ju and H. H. Liu, "A unified fuzzy framework for human-hand motion recognition," IEEE Trans. Fuzzy Systems, vol. 19, pp. 901-913, Oct 2011.

[16] Y.-H. Liu, H.-P. Huang, and C.-H. Weng, "Recognition of electromyographic signals using cascaded kernel learning machine," IEEE-ASME Trans. Mechatronics, vol. 12, pp. 253-264, Jun 2007.

[17] H.-B. Xie, Y.-P. Zheng, J.-Y. Guo, X. Chen, and J. Shi, "Estimation of wrist angle from sonomyography using support vector machine and artificial neural network models," Medical Engineering & Physics, vol. 31, pp. 384-391, Apr 2009.

[18] Z. Yan, Z. Wang, and H. Xie, "The application of mutual information-based feature selection and fuzzy LS-SVM-based classifier in motion classification," Computer Methods and Programs in Biomedicine, vol. 90, pp. 275-284, Jun 2008.

[19] J. A. Saglia, N. G. Tsagarakis, J. S. Dai, and D. G. Caldwell, "Control strategies for patient-assisted training using the ankle rehabilitation robot (ARBOT)," IEEE/ASME Trans. Mechatronics, pp. 1-10, 2012.

[20] J. Hu, Z. G. Hou, F. Zhang, Y. X. Chen, P. F. Li, and Ieee, "Training Strategies for a Lower Limb Rehabilitation Robot Based on Impedance Control," in 2012 Annual Int. Conf. IEEE Engineering in Medicine and Biology Society, ed, pp. 6032-6035, 2012.