Invariant Surface EMG Feature Against Varying Contraction Level for Myoelectric Control Based on Muscle Coordination

Jiayuan He, Student Member, IEEE, Dingguo Zhang, Senior Member, IEEE, Xinjun Sheng, Member, IEEE, Shunchong Li, Student Member, IEEE, and Xiangyang Zhu*, Member, IEEE

Abstract—Variations in muscle contraction effort have a substantial impact on performance of pattern recognition based myoelectric control. Though incorporating changes into training phase could decrease the effect, the training time would be increased and the clinical viability would be limited. The modulation of force relies on the coordination of multiple muscles, which provides a possibility to classify motions with different forces without adding extra training samples.

This work explored the property of muscle coordination in the frequency domain and found that the orientation of muscle activation pattern (MAP) vector of the frequency band is similar for the same motion with different force levels. Two novel features based on discrete Fourier transform and muscle coordination were proposed subsequently, and the classification accuracy was increased by around 11% compared to the traditional time domain (TD) feature sets when classifying nine classes of motions with three different force levels. Further analysis found that both features decreased the difference among different forces of the same motion (p < 0.005) and maintained the distance among different motions (p > 0.1). This study also provided a potential way for simultaneous classification of hand motions and forces without training at all force levels.

Index Terms—Electromyography, pattern recognition, force variation, prosthetic hands, muscle coordination, discrete Fourier transform.

I. INTRODUCTION

ELECTROMYOGRAPHY (EMG) signals represent muscle activity and are usually employed as an effective biological source for powered prostheses control [1]. Many commercial prostheses collect surface electromyography (sEMG) signals from a pair of muscles and employ a simple scheme based on the amplitude of sEMG to output activated functions. With this method, only one degree of freedom (DOF) can be controlled directly. If other DOF is expected, the user needs to switch the mode by co-contracting the muscle group. It makes the scheme non-intuitive and awkward to use in daily life [2].

To overcome these limitations, pattern recognition based control scheme has been explored in the last decades. Pattern recognition learns muscle contraction patterns in the training phase and outputs the intended movements during testing. It adopts more electrodes and provides intuitive control with more active DOFs [3]. Many state-of-the-art methods have been proposed and promising results have been achieved. Hudgins and Englehart developed features extracting different aspects of information from sEMG, including time-domain and frequency-domain, and combined them with effective classifiers [2], [4]–[6]. Other researchers also proposed many effective algorithms to achieve high classification accuracy [7]–[16].

However, one known disadvantage of this control scheme is that it does not accommodate changes in the contraction patterns. Classification performance achieved in the laboratory can not be repeated under the actual daily conditions. Changes of the pattern may be caused by physical or physiological variations, such as muscle fatigue, electrode shift, contraction intensity change, arm position movement, and so on [17], [18]. Recently, some researchers have made efforts towards this problem. Hargrove et al. studied the impact of electrode displacement and minimized the influence by optimizing the electrode configuration and expanding the training data set [19]. Fougher et al. investigated the effect of arm position and proposed to solve the problem by collecting training data from all the positions [20].

Efforts have also been made toward the solution for variations in muscle contraction. Al-Timemy et al. evaluated the effect of force variation on the performance of amputee subjects [21]. Tkach et al. analyzed the classification results of different time-domain features and found that the performance of all the features was affected by the changes of force [22]. Scheme et al. collected EMG signals of 10 motions with different force levels from 20% to 80% maximal voluntary contraction (MVC), and recommended to use data of 20% and 80% MVC to train the classifier to decrease the influence of force effect [23].

It is an effective method to incorporate each permutation of changes to training phase, but at the same time, it will prolong the training time and limit the clinical viability of the system [17]. If we can extract the invariant feature against contraction levels, it would be possible to maintain the performance without incorporating extra training samples. That will reduce the training time, and at the same time, make the whole system robust.

Muscle coordination addresses the question that how multiple muscles are activated in coordination to perform tasks [24]–[27]. Specially, the neural mechanisms underlying the
coordination of muscles for force production have been studied with some significant results [26], [27]. Valero-Cuevas studied the single-digit force production task and revealed that the EMG activity scaled linearly with force across multiple hand muscles [26]. Based on the work of Valero-cuevas, Poston et al. studied the three-digit grasp task and found that the finding also applied to the multiple-digit situation, i.e., EMG amplitude of hand muscles scaled uniformly as a function of grasp force for a given motion [27]. It means the coordination of hand muscles is invariant under a range of grasp forces. That makes it possible to extract information of force variations in muscle contraction.

Based on this property of muscle coordination, we proposed new features to classify motions with different force levels in this study. The differences among different contraction levels were decreased by a normalization step. Meanwhile, the variances among different motions were kept. The proposed features were robust to the changes of force levels, and as good as other classic features without variations in muscle contraction.

In the following section, we first introduced the collection of EMG signals with different force levels. Then the performance of new proposed features were evaluated and compared with other traditional features. The reason of performance improvement was investigated in the feature space. This study explored the coordination of muscles during force production further and its outcome would be beneficial to the design of robust control scheme based on pattern recognition.

II. METHODS

A. Data Collection

Nine able-bodied subjects participated in this study, all males with the age ranging from 20 to 30 years old. They were all healthy and had no reported history of neurological disorders. Informed consent was obtained from the subjects before the experiment. The procedures were in accordance with the Declaration of Helsinki.

The subjects were asked to sit in a height-adjustable chair. The sEMG signals were collected by a commercial myoelectric system (Trigno TM Wireless system, Delsys Inc., 20-450 Hz band pass filter). The sampling frequency was set to 2000 Hz. The skin was cleaned with alcohol to reduce impedance before data acquisition. Eight wireless electrodes were attached on the forearm muscles. The locations of electrodes were shown in Fig. 1.

The experiment contained eight classes of motions, tip prehension (TP), lateral prehension (LP), four-finger prehension grip (FP) and power grasp (PG), wrist extension (WE), wrist flexion (WF), wrist pronation (WP), wrist supination (WS), which were the desirable movements for amputees in daily life [28], [29], as shown in Fig 2. In addition, the rest state (RS) was considered as one class. Thus, it was a nine-class problem studied in this work.

The values of MVC of each motion needed to be obtained at the beginning of the experiment. The first four contractions (TP, LP, FP, PG) were measured by a set of commercial force sensors (Biometrics Ltd., UK), with 50 Hz sampling frequency. The other four contractions were measured by the custom-made equipment for measuring the wrist torque, as shown in Fig 3. The torque sensors were connected to the data acquisition device (USB-6343, National Instruments Corporation, USA) to record the signals. The sampling frequency was set to 1000 Hz. During performing the hand functions, the subjects were asked to put their arms on one box to keep their arms at the same height when performing wrist functions, which was for the avoidance of the limb position effect.

Fig. 1. Placement of wireless electrodes on the forearm: (a) anterior view, (b) posterior view. Channel 1 and Channel 2 are attached on flexor pollicis longus. Channel 3 and Channel 4 are placed on flexor digitorium superficialis and flexor digitorium profundus, respectively. The other channels from 5 to 8 are attached on abductor pollicis longus, extensor carpi radials, flexor carpi ulnaris and extensor digitorum, respectively.

Fig. 2. Eight classes of motions studied in the experiment: (a) tip prehension, (b) lateral prehension (c) four-finger prehension grip (d) power grasp, (e) wrist flexion, (f) wrist extension, (g) wrist pronation, (h) wrist supination. The first four motions are measured by the commercial dynamometer and pinchmeter. The other four motions are measured by the custom-made equipment.

For each motion, subjects were instructed to increase the isometric force as big as possible and maintain the contraction for 3 seconds. The procedure was repeated three times for each motion and the average value was used as the MVC of each class to which subsequent submaximal contraction tasks were referenced. The resting period between each MVC contraction was set to 3 minutes to avoid fatigue.

Three contraction levels were studied in our experiment, 20%, 50% and 80% MVC, which were defined as low, middle and high effort, respectively. The subjects were asked to perform each contraction by gradually increasing the exerted force to reach the target level and maintain the target contraction level for 5 seconds. One monitor was located in front of the subjects and visual feedback on the exerted force was provided.
The spectrum of sEMG signals commonly changes regarding different movements. There are a lot of methods to extract spectral information to discriminate motions. The direct way is to calculate magnitude averages in different frequency bands based on discrete Fourier transform (DFT). Suppose the whole frequency span is divided into six equi-width sub-bands because good performance on normal motion classification was reported using this approach. The sub-bands are 20-92, 92-163, 163-235, 235-307, 307-378, 378-450 Hz. This feature set is denoted as DFTR.

C. Muscle Coordination Representation

DFTR feature was extracted from each analysis window. For each sub-band the values were averaged across all samples for each combination of motion and force level. They were used to create an 8-dimensional (8-D) vector, representing the EMG pattern of all muscles for each frequency segment. The vector was referred to as a muscle activation pattern (MAP) vector, which represented the coordination pattern of muscles.

To quantify the degree of similarity in orientation between force levels within each band, we calculated the cosine of the angle between pairs of MAP vectors. Let MAP$_{i,x,m}$ denote the muscle activation pattern vector for motion $m$, force level $x$ and frequency band $i$. The similarity between force level $x$ and $y$ of the same motion for band $i$ is computed as

$$\frac{1}{8} \sum_{m=1}^{8} \cos < MAP_{i,x,m}, MAP_{i,y,m} > \quad (2)$$

where $\cos <,> \text{ denotes the dot product of two vectors normalized by the product of vector modules.}$ There are a total of three pairs of force level (20% vs. 50%, 20% vs. 80%, and 50% vs. 80%) to calculate.

The similarity between MAP vectors of different motions for band $i$ is computed as

$$\frac{1}{252} \sum_{m=1}^{8} \sum_{n=m+1}^{8} \sum_{x=1}^{3} \sum_{y=1}^{3} \cos < MAP_{i,x,m}, MAP_{i,y,n} > \quad (3)$$

It calculates the average cosine value of MAP pairs for different motions and contraction levels. The results are shown in Fig. 4.

For MAP vector pairs from the same motion, its cosine value is close to 1 for each frequency band, ranging from 0.862
to 0.927. It indicates that there is a high degree of similarity in orientation between pairs of MAP vectors of different force levels. Further comparisons reveal that MAP vectors associated with neighboring levels (20% vs. 50% and 50% vs. 80%) have a higher degree of similarity than that associated with forces which are further apart (20% vs. 80%). This means cosine values of the angle between MAP vector pairs decrease with increasing differences between force levels. The trend holds for all six frequency bands. On the other hand, the cosine value of vector pairs between different motions is about 0.48, which is significantly lower than that for the same motion.

Fig. 5 shows muscle activation pattern of eight motions for frequency band 163-235. Evidently, although the absolute value is different, the shapes of patterns for different contraction levels are similar in the radar chart. It demonstrated that forearm muscles were activated uniformly as a function of force when performing a certain task. The modulation of force only changes the magnitude of the pattern of muscle coordination. Meanwhile, the coordination pattern of muscles was different when performing different motions.

D. Feature Extraction

We have illustrated that it is similar in orientation of MAP vectors among different contraction levels of the same motion throughout all frequency bands. Based on this, we can modify DFTR features to classify motions with different force levels. The difference between vectors of different contraction levels of the same motion is the module of the vector. Two normalization methods were developed to remove the information of the module, and retain that of the angle. One is to normalize features across channels within each band. It is computed as

$$cnDFTR_{c,i} = \frac{DFTR_{c,i}}{\sqrt{\sum_{c=1}^{8} DFTR_{c,i}^2}}, \quad i = 1, 2, \ldots, L. \quad (4)$$

where $DFTR_{c,i}$ is the DFTR feature for channel $c$, frequency band $i$, and $cnDFTR_{c,i}$ is its normalization version. This process removes not only the module information, but also the ratio information between different frequency bands within the channel. It is denoted as channel normalization (cnDFTR).

The other method is computed as

$$gnDFTR_{c,i} = \frac{DFTR_{c,i}}{\sqrt{\sum_{c=1}^{8} \sum_{j=1}^{L} DFTR_{c,j}^2}}, \quad i = 1, 2, \ldots, L. \quad (5)$$

It only removes the module information and keeps the relation between different frequency bands within the channel. It is denoted as global normalization (gnDFTR).

E. Feature Space Quantification

We introduced two metrics based on [34] in order to quantify the changes of feature space after the normalization process. The distance within class ($D_{in}$) is defined to measure the distance between classes of different force levels of the same motion. It is given by

$$D_{in}(i) = \frac{1}{8} \sum_{m=1}^{8} \max_{j=1,2,3} \frac{1}{2} \times \sqrt{(\mu_{m,i} - \mu_{m,j})^T \left[ \frac{1}{2} (\Sigma_{m,i} + \Sigma_{m,j}) \right]^{-1} (\mu_{m,i} - \mu_{m,j})},$$

where $\mu_{m,i}$ is the centroid of motion $m$, force level $i$, and $\Sigma_{m,i}$ is its covariance. A bigger $D_{in}$ indicates a larger distance between classes of different forces for a given motion.
The distance between classes ($D_{out}$) is defined to measure the distance between classes of different motions. It is given by

$$D_{out}(i) = \frac{1}{8} \sum_{m=1}^{8} \min_{j=1,2,3;n=1,2,\ldots,8;n \neq m} \frac{1}{2} \times \sqrt{(\mu_{m,i} - \mu_{n,j})^T \left(\frac{1}{2} (\Sigma_{m,i} + \Sigma_{n,j})\right)^{-1} (\mu_{m,i} - \mu_{n,j})}. \tag{7}$$

It calculates the averages of Mahalanobis distance between different motions. A smaller $D_{out}$ means a shorter distance between classes of different motions. It is difficult for classification with the small value of $D_{out}$.

F. Feature Performance Evaluation

Classification error, defined as the percent of number of incorrect classified samples, was used to evaluate the feature performance. Linear discriminate analysis (LDA) was selected for its low computation cost, as it has been shown that the choice of classifier was not as crucial as the choice of feature set [6], [15], [35]. The performance of the proposed feature sets were compared to the traditional time domain (TD) features and one feature combination (waveform length, slope sign changes, log-detector, and nine-order AR coefficients), which was robust to contraction variations proposed in [22] and denoted as Comb in this study. The channel normalization method was also conducted on TD feature to test if it had effects on other features. The new feature was denoted as cnTD. For each kind of features (cnDFTR, gnDFTR, DFTR, TD, cnTD, Comb), the effects of training and testing with different force levels were reported and the improvement of performance was analyzed in the feature space.

Two-way ANOVA tests were conducted on the classification error to compare the performance of different features under different training and testing levels. The two factors were subject and feature (cnDFTR, gnDFTR, DFTR, TD, cnTD, Comb). Similarly, separate two-way ANOVA tests were applied on the metrics, $D_{in}$ and $D_{out}$, to test the effect of normalization method on DFTR and TD feature. The two factors were also subject and feature (cnDFTR, gnDFTR, DFTR for the test of effect on DFTR feature, cnTD, TD for that of TD feature). Tukey comparison was performed when significance was detected for the main factors. The significance level for all tests was set at 0.05.

III. RESULTS

A. Classification Results

Two-fold cross validation was used in this study. The results of classification error were shown in Fig. 6. For all the features, contraction variation increased classification errors. The classification error increased with increasing difference between training and testing force levels. The classifier trained at 50% force level achieved the best performance when it was tested with all three force levels. The classification errors averaged across all the conditions were 9.85%, 9.29%, 20.71%, 20.82%, 15.60% and 18.34% for cnDFTR, gnDFTR, DFTR, TD, cnTD and Comb feature, respectively. It can be seen that after the normalization process, the error rates of cnTD was decreased compared to TD. However, the extent of decrease is much lower than cnDFTR and gnDFTR (5% vs. 11%).

When the force levels of training and testing data were different, the classification errors of cnDFTR and gnDFTR were lower than other three features. The improvement was significant when the difference between training and testing force levels is large. For training at 20% and testing at 80%, the classification errors were decreased by about 18%. For training at 80% and testing at 20%, the classification errors were decreased by about 30%. Two-way ANOVA revealed that there was no significant interaction ($p > 0.4$) between two factors (subject and feature). The effects of feature sets were significant ($p < 0.01$) for all the conditions. Tukey comparisons showed that the performances of both cnDFTR and gnDFTR were significantly higher than other four features, except for the condition that training at 50% and testing at 80% compared to DFTR. There was significant difference between the performance of cnTD and TD for the following four conditions (training level vs. testing level), 20% vs. 80%, 50% vs. 20%, 80% vs. 20%, 80% vs. 50%.

There was a little increase in the error rate (~1.1% at 20%, ~0.7% at 50%, and ~0.4% at 80%) when training and testing at the same level for the performance of cnDFTR and gnDFTR compared to other four features. No significant interaction was
found between two factors \((p > 0.7)\). The effects of feature sets was not significant \((p > 0.05)\). Pairwise comparisons between cnDFTR or gnDFTR and other features showed that there was no significant difference except for the comparisons with Comb feature when training and testing at 20%.

There was no significant difference between the performance of cnDFTR and gnDFTR for all the conditions.

**B. Changes of Feature Space**

In order to describe changes in feature space after normalization, the distance within class and between classes were calculated for DFTR, cnDFTR, gnDFTR, TD and cnTD feature and the results were displayed in Fig. 7.

The distance within class was decreased for gnDFTR and cnDFTR, compared to DFTR at all force levels. For distance between classes, the performance of gnDFTR and cnDFTR were similar to DFTR. The effects of feature sets were only significant for \(D_{in}\) \((p < 0.005)\) for all three force levels. Tukey comparisons showed that \(D_{in}\) of cnDFTR and gnDFTR was significantly shorter than DFTR. However, there was no significant difference for the comparison between \(D_{out}\) of cnDFTR or gnDFTR and that of DFTR. No significant difference was found between the performance of cnDFTR and gnDFTR on both metrics for all the conditions. For cnTD and TD feature, both \(D_{in}\) and \(D_{out}\) of cnTD were increased compared to TD. Significant difference was found in statistics \((p < 0.001)\).

The results reveal that both normalization processes decrease the within-class distance while retaining between-class distance for DFTR feature. It indicates that normalization methods reduce the difference of different contraction levels for the same motion, and at the same time, retain the discrimination information between different motions. However, as for TD feature, the normalization methods increase both the distances within class and between classes. That made the performance of cnTD inferior to cnDFTR and gnDFTR.

Fig. 8 shows feature clusters and the LDA decision boundaries in the two-dimension feature space. The features are projected on the two most discriminatory dimension by linear discriminant analysis. The classifier was trained using data of 80% force level, and the boundaries represented the decision line between motion PG and FP. For DFTR feature, samples are misclassified at 20% force level between PG and FP. However, for cnDFTR and gnDFTR feature, clusters of other force levels for PG can be well separated from those for FP based on this boundary.

**IV. DISCUSSION**

Variations in muscle contraction cause a high degree of decrease on the performance of pattern-recognition based prostheses control. Though incorporating changes to training protocol could improve the classification accuracy, it will prolong the training time and increase the burden on users [17]. Our study exploited the property of muscle coordination and proposed new features to increase the overall classification performance from about 80% to 91%, which would make the system possible to be used in the real world [23].

The force production relies on the coordination of multiple hand muscles. Because of the redundancy of human musculature, there are many muscle coordination patterns to choose for central nervous system (CNS) to generate a given force. Previous study found that EMG amplitude of active muscles would scale uniformly as a function of force [27]. It revealed that muscle coordination patterns were similar through different forces for a given motion. Thus it provided a possibility to classify motions with different forces without training at all force levels. This study explored the frequency information and found that the orientation of MAP vectors for frequency band was highly correlated for comparisons of the same motion with different forces throughout eight hand motions. The difference in MAP vectors for force pairs further apart was larger than that for neighboring force levels. The large difference in MAP vectors for low force levels is likely due to the effect of the noise component that includes background neural activity from the CNS [36]. The degree of similarity in orientation for MAP vectors of different frequency band was overall very high throughout all force comparisons of the same motion, which was much greater than that of different motions.

Thus the information representing variations in contractions can be extracted, and enough information was remained for motion classification. Our work was inspired by the research [26] [27] and gained further insight into the frequency domain for muscle coordination.

Two novel features were proposed based on the property of muscle coordination to extract angle information and remove amplitude information from MAP vectors. Performances of both features were significantly better than that of the original feature, DFTR, which has a higher error rate \(\sim11\%\).
improvement was further investigated in the feature space, and it showed that both features reduced the differences between different force levels for the same motion, and maintained the effective variances between different motions. That confirmed the property of muscle coordination in the frequency domain from another aspect. For all the features, the classifier trained at 50% got the best performance among all the training levels (Fig. 6). So median contraction should be an optimal choice for robust training protocol.

When the same channel normalization technique was implemented on TD feature, there was a decrease in error rate of $\sim 5\%$, comparing to the original version. However, the extent of decrease for cnTD was much smaller than that for cnDFTR and gnDFTR (5% vs. 11%). The classification error of cnTD was also much higher than that of the proposed new features ($p < 0.05$). It indicated that the normalization method was more effective for the proposed features than TD feature sets in increasing robustness against changing force levels.

DFTR was essentially a sub-band power feature. Some other features, such as wavelet coefficients, wavelet packet, were also based on sub-band power and had been applied in myoelectric control [5], [6]. Given the success of the present study, it was expected that these features would also had similar advantage. However, a full investigation on this aspect was beyond the scope of this paper. The comparison between these features would discussed in the future study. The performance of the proposed feature sets were only tested on 200-ms window size. Considering the signals were from another aspect. For all the features, the classifier trained at 80% force level and the black line is the decision boundary between PG and FP. Data is from subject 1.

indicator that the power ratio among different channels, i.e. the coordination pattern of hand muscles, played an important role in motion classification. The module information and the power ratio between different frequency bands had little impact on classification errors.

It should be emphasized that all the results were obtained under the configuration where the EMG electrodes were attached on the specified muscles. One limitation of this configuration is that it may need time to detect the locations of muscles. If the electrodes are spaced around the forearm equally, the signals detected from the electrodes may not represent the activation of the specified muscles due to the crosstalk between channels. They represent the combination of signals from some neighboring muscles. The proposed method is not applicable in that situation. Blind source separation algorithms, proposed by Farina and Jiang, may provide a solution to this problem [12], [37].

Another potential application of this study is that it may provide a potential way to distinguish hand motions and levels of force simultaneously without training at all force levels. Prostheses control based on pattern recognition has been extensively investigated during the past 50 year [1]. However, most of the studies are focused on the identification of movements. For normal people, they can control not only the type of motions, but also the grade of force. Force control is also the requirement of amputees and will increase the user acceptance of myoelectric forearm prostheses [28]. Furthermore, it is also necessary for games or rehabilitation exercises [38]. Our study found that the force of prehension was related to the module of the MAP vector, and the type of motion was related to the angle of the MAP vector. If three degrees of force was available and the classifier was trained at the moderate force level, it might be possible to differentiate levels of contractions by comparing modules of MAP vectors. Users would be able to control motions and strength simultaneously without long training time. That would benefit the individuals with motor deficits and promote development of human-machine interface.

V. CONCLUSION

This paper presented new features which were robust to variations in contraction effort for pattern recognition-based
control scheme. The features were based on the property of muscle coordination in frequency domain and shown to outperform other four features. Two metrics were developed to describe changes of feature space for different feature sets.

The pattern recognition-based control scheme usually regards the musculoskeletal system as a black box. It does not utilize the knowledge of neurophysiological mechanism of natural movements [39]. EMG signals are an expression of neuromuscular activities which are controlled by CNS. So the changes of signals are related to the neural inputs of CNS. This study incorporated the mechanism of muscle coordination with the pattern recognition based framework and achieved promising results. The integration between neural mechanism and pattern recognition methods may provide a potential way to guarantee the robust performance and make the system clinically viable. Future work will focus on the incorporation of two parts and minimizing the effects of other disturbances on EMG pattern classification.

ACKNOWLEDGMENT

The authors would like to thank Jianwei Liu and Lizhi Pan for their constructive discussions and good advices. The authors would also like to thank all the subjects for their participation of the experiment.

REFERENCES


Jiayuan He received the Bachelor’s degree from the School of Mechanical and Electrical Engineering at Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2010. He is currently working toward the Master’s and Ph.D. degrees in the School of Mechanical Engineering at Shanghai Jiao Tong University, Shanghai, China.

His research interests include myoelectric signal processing and adaptive prosthesis control strategies.

Dingguo Zhang received the Bachelor’s degree in electrical engineering from Jilin University, China, in 2000, the Master’s degree in control engineering from Harbin Institute of Technology, China, in 2002, and the Ph.D. degree from Nanyang Technological University, Singapore, in 2007. From 2006 to 2007, he was a Research Fellow at Nanyang Technological University. In 2008, he was a Postdoctoral Fellow at LIRMM of CNRS, France.

He is currently an Associate Professor at the Institute of Robotics, Shanghai Jiao Tong University, China. His research interests include human-machine interface, rehabilitation technique, biological cybernetics, and biomechatronics. Dr. Zhang is a member of IEEE, RAS, EMBS, and IFESS. He is the winner of Delsys Prize 2011, USA.

Xinjun Sheng received the B.Sc., M.Sc. and Ph.D. degrees in mechanical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2000, 2003 and 2014. In 2012, he was a visiting scientist in Concordia University, Canada.

He is currently a lecturer in the School of Mechanical Engineering at Shanghai Jiao Tong University. His current research interests include robotics, and biomechatronics. Dr. Sheng is a member of IEEE, RAS, EMBS, and IES.

Shunchong Li received the Bachelor’s degree in mechanical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2007. He is currently working toward the Master’s and Ph.D. degrees in the School of Mechanical Engineering at Shanghai Jiao Tong University, Shanghai, China.

His research interests include myoelectric prothetic hand and EMG signal processing.

Xiangyang Zhu received the B.S. degree from the Department of Automatic Control Engineering, Nanjing Institute of Technology, Nanjing, China, in 1985, the M.Phil. degree in instrumentation engineering and the Ph.D. degree in automatic control engineering, both from Southeast University, Nanjing, China, in 1989 and 1992, respectively. From 1993 to 1994, he was a postdoctoral research fellow with Huazhong University of Science and Technology, Wuhan, China. He joined the Department of Mechanical Engineering as an associate professor, Southeast University, in 1995. Since June 2002, he has been with the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China, where he is currently a Changjiang Chair Professor and the director of the Robotics Institute. His current research interests include robotic manipulation planning, human-machine interfacing, and biomechatronics.

Dr. Zhu received the National Science Fund for Distinguished Young Scholars in 2005.