ELECTROTACTILE FEEDBACK BASED MUSCLE FATIGUE ALLEVIATION FOR HAND MANIPULATION

KAIRU LI*, YU ZHOU, DALIN ZHOU, YINFENG FANG, JUNYOU YANG, HONGHAI LIU

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Tactile feedback is beneficial to improve the hand prosthesis performance, alleviate phantom pain, reduce muscle fatigue, etc. During the manipulation process, muscle fatigue not only causes discomfort to prosthesis users but also disturbs the sEMG-based motion recognition, which significantly deteriorates the prosthesis functional performance. Efforts have been made to explore appropriate signal processing algorithms which could be less influenced by muscle fatigue. However, few studies concern how to alleviate muscle fatigue directly. Thus, this study proposes a novel method to avoid excessive muscle fatigue based on electrotactile feedback. A portable electrotactile stimulator is developed with adjustable parameters, multiple channels and wireless communication. It is implemented in a virtual hand grasping platform driven by sEMG signals to investigate the impact of tactile feedback on muscle fatigue. Experiment results show a higher success rate of grasping with electrotactile feedback than that with no feedback. Moreover, compared with grasp in the no feedback condition, an observable decrease of sEMG intensity when grasping a heavy object with electrotactile feedback, despite a comparable performance on the light and medium objects in both feedback conditions. It indicates that tactile feedback helps to alleviate muscle fatigue caused by excessive muscle contraction, especially when large strength is needed.

Keywords: Electrotactile stimulator; grasping force control; muscle fatigue; tactile feedback.

1. Introduction

Transradial amputees may benefit from tactile feedback in improving prostheses performance, reducing phantom pain, enhancing a sense of embodiment, alleviating muscle fatigue, and so on. However, existing prosthetic hands have not been effectively equipped with tactile feedback. Apart from a compromise of manipulation performance and user experience, amputees intuitively tend to apply excessive

Kairu Li and Junyou Yang are with the School of Electrical Engineering, Shenyang University of Technology, Shenyang, 110870, China (e-mail: Kairu.Li@sut.edu.cn, junyouyang@sut.edu.cn). Yu Zhou and Honghai Liu are with the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, 200240, CHN (e-mail: hnlyu@sjtu.edu.cn, honghai.liu@icloud.com). Dalin Zhou is with the School of Computing, University of Portsmouth, Portsmouth, PO1 3HE, UK (e-mail: Dalin.Zhou@port.ac.uk).

attention and strength to complete daily tasks due to the absence of tactile sensation, which easily causes muscle fatigue and increases the unnecessary manipulation burden. The feeling of fatigue and tiredness limits the user's continuous using time. Some efforts have been devoted to reducing the hand manipulation burden by sensory feedback. A haptic transplant technology was proposed to achieve an intuitive control of a hand prosthesis by delivering force feedback to the user's residual body¹. A haptic device was also applied to aid a teleoperation system². Additionally, muscle fatigue may deteriorate the performance of surface electromyographic (sEMG) pattern recognition. Among all the feasible modalities, sEMG has been most exploited for its easy access, intuitive relation to motor function, and natural manifestation for grasp force prediction^{3,4,5}, so that sEMG-based motion recognition has become a common method to decode the user's intention for prosthesis control in recent decades. However, muscle fatigue will decrease the sEMG features decoding rate and affect the manipulation performance. Most existing studies focused on testing proper sEMG features which were robust to the influence of muscle fatigue^{6,7}, while few studies concern methods to alleviate the user's muscle fatigue actively. Based on the assumption that there is a positive relation between muscle fatigue and the force applied during hand manipulation, tactile feedback is suggested to be effective on muscle fatigue alleviation by avoiding excessive manipulation force.

For the integration of tactile feedback in hand prostheses and rehabilitation systems, it is important to develop a wearable tactile stimulation device. Among various tactile stimulation techniques, electrotactile stimulation outperforms the rest with several advantages and a considerable number of related studies⁸. An exploitation of electrotactile stimulation has contributed to phantom limb sensation⁹, prosthesis control¹⁰, etc. This research is inspired by the success of electrotactile feedback on force control¹¹. A flexible electrotactile device that allows a deeper insight into the tactile feedback assisted grasp force control is still desired despite the efforts made in academia. For example, a high-voltage stimulator was designed with a maximum output of 25 mA¹². However, its stimulation current is monophasic, which made it not suitable for long-term stimulation due to the lack of the negative stimulation phase to eliminate the electrical charge accumulation in the skin to avoid tissue damage. Schaning *et al.* developed a single channel electrotactile stimulator with high-performance bipolar transconductance amplifier which could output the current up to ± 20 mA¹³. Commercial stimulators, such as the Master-9 (A.M.P.I. Company, Israel), STMISOLA (BIOPAC Systems, CA), TENS 7000 (VQ OrthoCare, CA), STG4008 (Multi Channel Systems, Germany) and so on are also available. However, they suffer from high power consumption, bulky size, a limited number of output channels or high cost. To overcome the limitations, a portable, multichannel and programmable electrotactile stimulator with wireless communication is desired for daily use, rehabilitation and virtual reality applications.

Thus, this study aims to develop a portable multi-channel electrotactile stimulator and then implement it in an sEMG-driven virtual hand grasping platform to investigate the impact of tactile feedback on avoiding excessive muscle fatigue during

hand grasping process. sEMG-based hand motion recognition and force estimation algorithms are applied for the hand control in the virtual grasping environment. The remaining parts of this paper are organized as follows. Section 2 presents the details of the electrotactile stimulator design. The experimental platform establishment including the virtual hand environment and sEMG-based hand motion recognition and force estimation is introduced in Section 3. Experiment and results are given in Section 4, followed by a conclusion in Section 5.

2. Development of Electrotactile Stimulator

2.1. System construction

The construction schematic of the electrotactile stimulator is presented in Fig. 1. The stimulator consists of six parts: the graphical user interface (GUI), power supply module (PSM), Bluetooth module (BM), microcontroller unit (MCU, STM32F103VCT6, STMicroelectronics), electric stimulator module (ESM) and the electronic switch (ES). The GUI is responsible for the configuration of stimulation parameters and the communication with the hardware via the BM. The stimulator is powered by an independent +12V DC battery. Constant-current output mode is employed in the stimulator. To ensure a stable and constant stimulation output under different load, the voltage is boosted from +12V to +120V by a DC-to-DC converter to supply the following constant current source (CCS) module. Meanwhile, the power is also converted by a voltage regulator to +5V to supply the BM. Then, the +5V is converted to +3.3V by a voltage regulator to supply the MCU. Additionally, the +12V is boosted to +26V by a voltage regulator to supply the operational amplifier LM358 in the CCS. The ESM is a main functional module of the stimulator, consisting of an amplifying circuit (AC), the CCS and a bridge circuit (BC). The AC is designed to provide the reference voltage for the control of the positive and negative phase of the current's amplitude, according to the digital-to-analogue converter (DAC) output based on an in-phase operational amplifier circuit from the MCU. By the cooperation of three components, the ESM generates symmetric-biphasic square wave current with an adjustable setting of frequency, amplitude and pulse width and outputs through the multi-channel ES.

2.2. Multi-channel Control

There are 16 channels in total of the electrotactile stimulator, which enables complex multichannel tactile decoding. The ES is designed based a solid-state relay AQW216 (Matsushita Electric Works, Ltd) under the control of MCU. It is applied to switch among different channels of electrodes to output the stimulation current generated by the ESM. Each channel can be controlled independently. Consequently, the multi-channel stimulation is realised as shown in Fig. 2.

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Fig. 1. Schematic of the electrotactile stimulation.

Fig. 2. Schematic of the electronic switch (ES) control circuit. The positive phase and the negative phase of the stimulation current are generated by the bridge circuit (BC).

2.3. Amplitude control

The constant-voltage output, constant-current output and the hybrid output are the output modes widely utilised in the design of electrical stimulation systems¹⁴. The constant-current output is employed in the proposed stimulator because of its better robustness with the skin resistance variation than that of the constant-voltage output¹⁵. Fig. 3 presents the structure of the CCS. The current amplitude can be calculated according to (1).

$$I_d = \frac{R_2 U_{REF}}{(R_2 + R_3) R_s} \quad (1)$$

where U_{REF} is the reference voltage (the amplified DAC signals) and R_s is used to monitor the output current amplitude in real time.

2.4. Waveform control

The BC is designed to realise a biphasic square stimulation waveform. As shown in Fig. 4, the optocouplers are used to isolate the control signals from the analogue circuit to avoid the crosstalk from the high voltage side. They also act as the switches between the CCS and high voltage (e.g. Opt 1 and Opt 2) and between

Fig. 3. Schematic of the constant-current source (CCS). The LM358 consists of two independent and high-gain operational amplifiers which are used to set up the feedback network for the maintain of the constant current.

the reference voltage and the CCS (e.g. Opt 3 and Opt 4). Thus, the stimulation current parameters can be determined by the pulse width modulation (PWM) signals (in terms of frequency and pulse width) and the reference voltage (in terms of amplitude).

Fig. 4. Schematic of the bridge circuit (BC). Opt 1 to Opt 4 represent four optocouplers.

When Opt 1 and Opt 4 are switched on together, the CCS2 starts working and generates positive square wave current. The high level overlap of PWM1 and PWM4 determine the positive phase's pulse width, while the amplitude is determined by U'_{REF2} whose value is equal to U_{REF} when PWM4 is at the high level. In a similar way, the negative phase is generated when the CCS1 is turned on. Thus, the stimulation frequency remains the same as PWM signals. The symmetric-biphasic stimulation pulses can be achieved when the length of the high level overlap of PWM1 and PWM4 is the same as that of PWM2 and PWM3. To avoid the conflict

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of the out-of-phase stimulation current, an interval time of $100 \mu\text{s}$ is set between the positive and negative phase.

2.5. Output test

The output capability of the proposed stimulator was tested when the load resistance ranged from 200Ω to $3 \text{ k}\Omega$. Amplitudes of 4 mA and 8 mA were chosen to be tested, because the electrotactile stimulation intensity should be lower than the motor threshold, which is generally approximately higher than 10 mA . The theoretical voltage values were calculated by $I \times R_{load}$, while the measured values represented the actual voltage measured on load resistance. The test results are shown in Fig. 5. The root-mean-square errors (RMSE) of the output of 8 mA and 4 mA are 0.43 V and 1.22 V , respectively. It revealed that the stimulator demonstrates satisfactory constant-current output performance which is comparable with the stimulators mentioned in ^{12,13}. Moreover, the higher the output is, the higher amplitude control accuracy will be achieved by the proposed stimulator.

Fig. 5. Output capability test of the electrotactile stimulator.

3. Experimental Platform Establishment

To validate the effectiveness of tactile feedback on muscle fatigue alleviation, an integrated platform is established to support the experiments of virtual grasping with no feedback and electrotactile feedback.

3.1. Platform Construction

A typical experimental setup is presented in Fig. 6, which consists of a virtual grasping environment, an sEMG acquisition module and the aforementioned electrotactile stimulation module. During the experiment, the subject will try to conduct grasp gesture with the empty left hand. Two pairs of sEMG electrodes are attached on the left forearm to extract sEMG signals for the virtual hand's motion control and grasping force estimation. In the condition of electrotactile feedback, the intensity

of the virtual grasping force will be fed back to the subject's right arm by 3 pairs of electrodes.

Fig. 6. Experimental setup. The integrated virtual grasping platform includes an sEMG acquisition module, virtual grasping environment and the proposed electro tactile stimulation module.

3.2. Virtual Hand Environment

The virtual hand environment integrates the other two modules and provides a simulation of the hand grasping process to subjects. A basic hand simulator is applied in the virtual environment¹⁶. A ball with adjustable weight (light, medium, heavy) is set as the grasping target. The subject needs to apply proper grasping force to achieve a successful grasp of each object according to its weight. The interface also provides a force bar to display the real-time grasping force variation and a scale to indicate the least lifting force. Grasp results are displayed in the board of upper-left corner.

3.3. sEMG-based Hand Motion Recognition

An intuitive control of the virtual hand relies on the accurate recognition of motion intention and corresponding force exertion. A hierarchical recognition framework comprising both hand motion and force recognition is applied in this research. SEMG based pattern recognition is adopted for the recognition of the user's hand motion intention, which is in alignment with the claimed superiority of pattern recognition over direct control¹⁷. Raw sEMG signals are first captured from superficial muscle contractions and filtered by a band-pass Butterworth filter and a notch filter respectively to remove the noises attributed to power line interference and the components less related to the hand motion. Then the filtered sEMG stream is segmented by overlapped windows where each segment contributes to a recognised motion type for execution. Classic pattern recognition operations are conducted

on the sEMG segments where features are extracted and classified into predefined motion types. The corresponding force exertion for the recognised hand motions is finally recognised through a regression model. Specifically, the grasp force is estimated proportionally to the intensity of sEMG signals in this paper to reveal the influence on continuous muscle contraction control.

To improve the reliability of the hand motion recognition in the virtual platform, a redundant feature extraction strategy in combination with a regularised classifier are chosen in the current evaluation. The classic Hudgins' time domain features proposed in the cornerstone paper¹⁸ in combination with the autoregressive coefficients, recognised as TDAR features are adopted as the feature extraction in this research. The TDAR features have been mostly exploited in pattern recognition based hand motion rehabilitation and remained the state-of-the-art for their less computational cost and relatively robust performance in long-term use. The TDAR features including mean absolute value, waveform length, zero crossings and slope sign changes together with 4-th order autoregressive coefficients (AR) are adopted as the sEMG signal patterns in the proposed platform. Different from conventional singly segmented feature extraction, a multi-length segmented feature extraction scheme¹⁹ is utilised in this paper, which comprises the segment windows with the length/increment size of 200/10 ms, 150/20 ms and 100/50 ms respectively and contributes to a total of 2176-dimensional feature candidates. The extracted features are then fed to the classifiers for hand motion recognition.

Despite the well-recognised feasibility of linear discriminant analysis (LDA) classifier in sEMG based hand motion recognition²⁰, the redundancy brought up by the multi-length segmentation is not well accommodated. Thus, a well-designed classifier is required to simultaneously exploit the redundancy and avoid the overfitting on closely related time domain features. The explicit feature selection in combination with the conventional LDA inevitably leads to more computational cost for each individual subject. An intuitive idea is to utilise some efficient regularisation schemes instead of the explicit feature selection process. Ye²¹ proposed the least squares formulation of LDA (LS-LDA) for multi-class classifications under a mild condition. Given N labelled training samples of $\{(x_1, l_1), (x_2, l_2), \dots, (x_N, l_N)\}$, where $x_i \in \mathbb{R}^d$ and $l_i \in \{1, 2, \dots, k\}$ are d -dimensional data vectors and corresponding labels within k classes, respectively. The multiclass LDA can be formulated into a multivariate linear regression problem equivalent to the minimisation of the objective function in (2).

$$L(W) = \frac{1}{2} \|X^T W - Y\|_F^2 \quad (2)$$

where $\|\cdot\|_F$ is the Frobenius norm. $W = [w_1, w_2, \dots, w_k] \in \mathbb{R}^{d \times k}$ is the weight matrix to be solved. $X = [x_1, x_2, \dots, x_N] \in \mathbb{R}^{d \times N}$ is the pooled samples whose column represents the feature vector of a sample, and $Y \in \mathbb{R}^{N \times k}$ is the k -class

indicator matrix defined in (3).

$$Y_{ij} = \begin{cases} \sqrt{\frac{N}{N_j}} - \sqrt{\frac{N_j}{N}}, & l_i = j \\ -\sqrt{\frac{N_j}{N}}, & otherwise \end{cases} \quad (3)$$

where N is the total number of labelled training samples, and N_j is the number of samples belonging to class j . The weight matrix W can be routinely calculated by its closed-form least square solution in (4).

$$W = X^\dagger Y \quad (4)$$

where $X^\dagger$ is the pseudoinverse of X . Thus, the training of a conventional LDA is equivalent to calculating the weight matrix W from the pooled data with the class indicator matrix Y generated from the original labels. Besides, the least square formulation allows an explicit incorporation of the regularisation on the coefficients to constraint the contribution of each feature to the prediction. A typical formulation of the regularised LS-LDA is written in the form of (5).

$$F(W) = \frac{1}{2} \|X^T W - Y\|_F^2 + \alpha \Phi(W) \quad (5)$$

where α controls the trade-off between the regularisation term $\Phi(W)$ and the loss term. Specifically, the regulariser on the coefficients can be incorporated as an implicit feature selection module. The i -th row of the LS-LDA coefficient matrix W corresponds to the contribution of i -th feature of the input feature vectors in all samples. A shared sparse feature representation is simultaneously selected together with the LS-LDA prediction by minimising the $l_{2,1}$ -norm regularised objective function in (6).

$$F(W) = \frac{1}{2} \sum_{i=1}^d \|w_i^T X - y_i^T\|_2^2 + \alpha \|W\|_{2,1} \quad (6)$$

The $l_{2,1}$ -norm $\|\cdot\|_{2,1}$ is defined as the accumulated Euclidean norm of each row vector within.

$$\|W\|_{2,1} = \sum_{i=1}^N \|w^i\|_2 \quad (7)$$

where w^i is the i -th row of the coefficient matrix W . The minimisation of the $l_{2,1}$ -norm intuitively leads to a reduced number of non-zero rows. Due to the convex nature of both the loss term and regularisation term, the objective function defined in 6 is convex itself. The minimisation of the objective function is rewritten by adding an auxiliary variable Z in (8).

$$\begin{aligned} \min & \frac{1}{2} \sum_{i=1}^d \|w_i^T X - y_i^T\|_2^2 + \alpha \|Z\|_{2,1} \\ \text{s. t. } & W = Z \end{aligned} \quad (8)$$

The corresponding augmented Lagrangian is then formed in (9).

$$L(W, Z, \lambda) = \frac{1}{2} \sum_{i=1}^d \|w_i^T X - y_i^T\|_2^2 + \alpha \|Z\|_{2,1} - \text{Tr} [\Lambda^T (W - Z)] + \frac{\beta}{2} \|W - Z\|_F^2 \quad (9)$$

where Λ is the Lagrange multiplier and β is the penalty parameter. The alternating direction method²² is subsequently applied to solve the minimisation problem comprising a 3-step loop of minimisation and multiplier update shown in (10)-(12) until convergence.

$$W^{k+1} = \arg \min_W L_\beta(W, Z^k, \Lambda^K) \quad (10)$$

$$Z^{k+1} = \arg \min_Z L_\beta(W^{k+1}, Z, \Lambda^K) \quad (11)$$

$$\Lambda^{k+1} = \Lambda^K + \beta(W^{k+1} - Z^{k+1}) \quad (12)$$

The motion prediction is conducted according to the regularised LS-LDA model with the converged solution. The sparse coefficient matrix controls the contribution of each feature type and remedy the over-fitting of same types of feature extraction strategies under various segments. Besides, it utilises the most of the hand motion related knowledge where enumeration of the zero crossings and slope sign changes resides in. Then the grasp force under the recognised hand motion is estimated using its pre-trained regression model. Finally, the virtual hand is controlled and visually displayed with the input of both hand motion and grasp force in real time.

4. Experiments

The experiment aims to evaluate the impact of electrotactile feedback on alleviating muscle fatigue by saving the intuitive muscle contraction during hand grasping process. The experimental protocol is described in this section followed by results and analysis.

4.1. *Experimental Procedure*

The aim and procedure of the experiment were explained to subjects and they signed a consent form before the experiment. Six able-bodied subjects (23-28 years old) participated in the experiment. The study was approved by the local ethical committee.

Before the experiment, each subject was prepared with two pairs of sEMG electrodes on the left forearm and three pairs of electrotactile stimulation electrodes on the right arm. Then, he/she was asked to contract left arm muscles by grasping with an empty hand to set the maximum of the virtual grasping force and initial parameters of 9-level electrotactile stimulation. These stimulation coding scheme would be further adjusted according to the subject's feedback until he/she could

identify all the stimulation levels without discomfort. Finally, the subject had one minute to freely conduct virtual grasps with electrotactile feedback and get familiar with the experimental platform by observing its visual interface simultaneously.

Based on the above preparation, the subject would be trained and tested in non-feedback condition and electrotactile feedback condition, respectively. In each trail, he/she would grasped with an empty hand for 2.5 seconds. A successful grasp was defined as that the last-2-second-average sEMG intensity was above the lifting force threshold. Meanwhile, the ball turned to green to indicate a successful trail. Otherwise, it was considered as a failed trial and the ball correspondingly turned to red.

(i) Virtual grasping with no feedback

Firstly, the subject was trained to conduct virtual grasps via contracting arm muscles with 3 grades of strength, which simulated grasps of 3 objects of different weights—object 1 (light), object 2 (medium) and object 3 (heavy). By observing the force bar, the subject conducted grasp with an empty hand and controlled muscle contraction strength to make sure the virtual grasping force above the lifting threshold. One minute was provided to the subject to practice for each object. Then, the force bar was hidden, and the subject was asked to perform virtual grasping attempts based on experience. After each attempt, the subject could observe the result through the object's state as shown in Fig. 6, so that he/she could adjust arm contraction strength in the next attempt. The subject was considered to master the force control for each object after two successful grasps in a row. The sEMG-signal intensity and the total numbers of attempts for each object in the training stage were recorded. Next, during the testing process, objects of different weights were presented randomly for 30 times (10 times for each object) to the subject who conducted grasps with no feedback. Results of all testing trials were recorded.

(ii) Virtual grasping with electrotactile feedback

Before the experiment with electrotactile feedback, the stimulation parameters determined previously should be double-checked to ensure that the subject could learn and identify all stimulation levels. A detailed description of the method of parameter adjustment and the criterion of subject training please refer to Li's research²³. Then, the experimental procedure of training and testing with electrotactile feedback was similar to the virtual grasping with no feedback, but the subject could tell and adjust his/her muscle contraction strength according to the electrotactile stimulation levels on the basis of a closed-loop control.

4.2. Results and Analysis

The variation of sEMG intensity in a typical training process of a subject is demonstrated in Fig. 7. In the condition of no feedback as shown in Fig. 7(a), the subject adjusted the grasping force according to the previous attempt and finally achieved

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the goal in several steps. While in the condition of electrotactile feedback as shown in Fig. 7(b), the subject could rely on the stimulation which indicated the force intensity in real time. Comparable attempt numbers were observed in both conditions, given the simple experimental setting of success and failure.

Fig. 7. Typical training results of a subject: (a) with no tactile feedback and (b) with electrotactile feedback. The attempts with the same object are grouped by a dotted line. The lifting force thresholds are marked by short horizontal lines. The successful grasps and failed attempts are marked by green points and red points, respectively.

The average normalised sEMG intensity of all the subjects during the training process is presented in Fig. 8. There is no significant intensity difference between the two conditions, although the average sEMG intensity with no feedback is slightly higher than the intensity with electrotactile feedback.

Fig. 8. Average normalised sEMG intensity during the training process

The success rates of testing stage are listed in Table 1. It can be seen that the virtual grasp with electrotactile feedback has a better performance than that with no feedback, especially when grasping the heavy object. Given that the subjects

could complete a successful grasp simply by contracting their muscle hard enough, they could also achieve a satisfied success rate in the non-feedback condition.

Table 1. Testing success rate

Success rate	Light	Medium	Heavy
No feedback	0.89	0.73	0.72
Electrotactile feedback	0.88	0.76	0.79

The average normalised sEMG intensity of the successful attempts of all the subjects during the testing process is presented in Fig. 9. The results on the light object and the medium object are comparable in both conditions. However, the sEMG intensity spent on the heavy object in electrotactile feedback condition is observably less than that in no feedback condition. The sEMG intensity is considered to be positively related to the strength of muscle contraction and further related to fatigue. Thus, the integration of tactile feedback is beneficial to muscle fatigue alleviation, especially when a large grasping force is required.

Fig. 9. Average normalised sEMG intensity during the testing process

5. Conclusion

This paper proposed a novel electrotactile stimulator and implemented it on a virtual grasping platform to investigate the impact of electrotactile feedback on muscle fatigue alleviation. The portable, multichannel and programmable electrotactile stimulator with wireless communication, as a human-machine interface, is potential to be applied in rehabilitation and virtual reality to supply tactile feedback. By comparing the grasping sEMG intensity in the conditions of no feedback and electrotactile feedback, the experimental results show that the subjects spent less muscle strength with electrotactile feedback than those in the condition of no

feedback. Thus, the electrotactile feedback is effective to avoid excessive grasping strength and reduce the prosthesis user's manipulation burden and muscle fatigue.

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Kairu Li received her M.S. degree in Control Theory and Control Engineering and B.S. degree in Automation from Dalian University of Technology, China, in 2015 and 2012, respectively. She received her Ph.D. degree in Intelligent System and Biomedical Robotics from the University of Portsmouth, U.K., in 2018. Then, she held the position of Senior Research Associate with the University of Portsmouth. From 2019

to now, she is an associate professor at the School of Electrical Engineering, Shenyang University of Technology. Her research interests include wearable sensor systems, electrotactile stimulation, sensory feedback in prosthetics and rehabilitation.

First-Author is the author of over X technical publications, proceedings, editorials and books. His/her research interests include Mind topics, Body topics and Application topics (see IJHR’s flyer). He/she is the coordinator of the collaborative research network on Humanoid Robots at the University of Name, Country. He/she is an active member of the Y Societies, and was the General Chair

of Z Conferences in Country, and the Co-Chair of Z Conferences in Country.

Yu Zhou received the B.S. degree from the College of Mechanical and Electrical Engineering, Central South University, Changsha, China, in 2014. He is currently working toward the Ph.D. degree in the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China. His research interests include intelligent system, biological signal processing and electrical stimulation.

Yinfeng Fang received the M.S. degree in pattern recognition and intelligent system from the Zhejiang University of Technology, Hangzhou, China, in 2012, and the Ph.D. degree in computer science from the University of Portsmouth, Portsmouth, U.K. 2015. He joined the Intelligent System and Biomedical Robotics Group, University of Portsmouth, in 2015, as a Senior Research Associate. His research interest is on bio-signal acquisition and processing, humanmachine interface, and machine learning.

Honghai Liu received the Ph.D. degree in robotics from King's College London, London, U.K., in 2003. He joined the University of Portsmouth, Portsmouth, U.K., in September 2005. He previously held the position of research appointments with the Universities of London and Aberdeen, as well as Project Leader appointments in the large-scale industrial control and system integration industry. His current research interests include biomechanics, intelligent sensing, pattern recognition, intelligent video analytics and wearable robotics and their practical applications with an emphasis on approaches that could make contributions to the intelligent connection of perception to action using contextual information. He has published numerous peer-reviewed international journal and conference papers and received four best paper awards. Dr. Liu is an Associate Editor of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS and the IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS.