UNIVERSITY OF LEEDS

Proceedings Paper:
Liu, Q, Ma, L, Ai, Q et al. (2 more authors) (2018) Knee Joint Angle Prediction Based on Muscle Synergy Theory and Generalized Regression Neural Network. In: 2018 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM). IEEE/ASME International Conference on AIM, 09-12 Jul 2018, Auckland, New Zealand. IEEE , pp. 28-32. ISBN 9781538618547

https://doi.org/10.1109/AIM.2018.8452230

Knee Joint Angle Prediction Based on Muscle Synergy Theory and Generalized Regression Neural Network *

Quan Liu, Liangyun Ma, Qingsong Ai, Kun Chen, and Wei Meng, *Member, IEEE*

Abstract—**Continuous joint motion estimation plays an important part in accomplishing more compliant and safer human-machine interaction (HMI). Surface electromyogram (sEMG) signals, which contain abundant motion information, can be used as a source for continuous joint motion estimation. In this paper, a knee joint angle prediction system based on muscle synergy theory and generalized regression neural network (GRNN) was proposed. The wavelet transform threshold method was used for sEMG signals and angle trajectories denoising. The time-domain features wave-length extracted from four-channel sEMG signals were decomposed into a synergy matrix and an activation coefficient matrix by using nonnegative matrix factorization based on muscle synergy theory. A GRNN based on golden-section search was employed to build the activation model mapping from the activation coefficients to the knee joint angles, so as to realize the continuous knee joint angle estimation. The experimental results show that the average coefficient of determination is 0.933. In addition, a user graphic interface based on the Java platform was designed to display the dynamic sEMG data and predicted knee joint angles in real time.**

I. Introduction

Surface electromyogram (sEMG) signals are electric potentials generated by the neurologically activated muscle cells, which contain abundant motion information. Constructing a human-machine interaction (HMI) system with sEMG signals can realize a natural control similar to the brain control, which is more acceptable to users. sEMG acquisition is noninvasive, and the acquisition technology is increasingly sophisticated. Besides, sEMG signals rely on muscles that drive movements, rather than organs that execute movements, which is more propitious to the handicapped. Therefore, it is reasonable, effective and feasible to realize HMI systems based on sEMG analysis.

The key to realize HMI systems based on sEMG is to accurately identify human motion intentions. sEMG-based motion intent recognition methods include discrete modes classification and continuous motion estimation. S. Amsüss et al. [1] proposed a post-processing algorithm based on linear discriminant analysis and artificial neural network (ANN) that could detect and correct the wrong classification. The method improves the accuracy by 4.8%~31.6%. T. Matsubara et al. [2] proposed a multiuser myoelectric interface based on a bilinear sEMG model that could easily adapt to new users. The method results in 73% accuracy when it is applied to a recognition task of five hand gestures. J. Liu and P. Zhou [3] compared the recognition accuracy of different feature sets and classifiers (linear discriminant analysis and 5-nearest neighbor) towards six hand-grasp movements of incomplete cervical spinal cord injury patients. Results show that each average classification accuracy can reach more than 97%. However, discrete modes classification can only identify a small number of discrete movements, which cannot sustain the continuous matching. In addition, the types of movements are predefined and the real situation is seldom considered, thereby reducing the system's functionality and security. Therefore, continuous motion estimation is more meaningful for the natural control of HMI.

Currently, sEMG-based continuous motion estimation includes two methods: kinetic model methods and regression model methods. J. Han et al. [4] constructed a state-space sEMG model based on Hill's muscle model for continuous estimation of the elbow joint angle and angular velocity. E.E. Cavallaro et al. [5] constructed a sEMG-based HMI by using an optimized Hill's muscle model based on genetic algorithms, which resulted in a high correlation between the predicted results of the model and the measured data. M. Pang et al. [6] presented a Hill-type-based muscular model and a state switching model for the continuous estimation of elbow joint angle, and the predicted results were used to control an exoskeleton device. S. Zhang et al. [7] proposed a forearm muscle strength estimation method based on musculoskeletal model with Bayesian linear regression algorithm for calibrating parameters. Although, kinetic model can well explain the process of motion generation, it requires more human parameters to be measured and some of these parameters cannot be directly measured, which leads to a complex modeling process. Regression model methods, which have a straightforward modeling process, do not restrict the application of sEMG. ANN is one of the most commonly used regression model methods, it has good nonlinear performance, and it is especially suitable for nonlinear input signals. G. Cheron et al. [8] designed a fully connected dynamic recurrent neural network for estimation of the elevation angles of the three main lower limb segments (thigh, shank and foot). F. Zhang et al. [9] constructed a Back-Propagation Neural Networks (BPNN) to create a mapping between sEMG signals and joint angles of hip, knee and ankle, which could be used to predict joint movements of lower extremities and achieve self-control of lower-limb rehabilitation equipment. L. Tong et al. [10] proposed a lower limb joint angle estimation model based on BPNN and autoregressive algorithm, which resulted in mean angle root mean square error of 4.27◦. R. Raj and K. Sivanandan [11] proposed a continuous estimation method for elbow joint angle and angular velocity by using multiple layer

* Research supported by the National Natural Science Foundation of China (Grant No. 51705381 and Grant No. 51475342) and the Fundamental Research Funds for the Central Universities (Grant No. 2017-IVA-051).

Q. Liu, L. Ma, Q. Ai, K. Chen and W. Meng (corresponding author to provide phone: +86-131-6331-2360) are with the School of Information Engineering, Wuhan University of Technology, Wuhan, China. (e-mails: {quanliu, miama, qingsongai, kunchen, weimeng}@whut.edu.cn). W. Meng is also with the School of Electronic and Electrical Engineering, University of Leeds, LS2 9JT, UK. (email: w.meng@leeds.ac.uk)

perceptron neural network based on nonlinear auto regression with exogenous inputs. However, regression model methods proposed so far have insufficiently used the physiological characteristics of the human body. Moreover, ANN entirely depends on training data, which may result in a poor generalization ability.

In order to use physiological features of sEMG signals more sufficiently and better describe the intrinsic physiological-physical relationship between sEMG signals and human motions, this paper proposed a knee joint angle prediction method based on muscle synergy theory and generalized regression neural network (GRNN), which made full use of the control relationship between the central nervous system (CNS) and muscle tissues. By using the nonnegative matrix factorization (NMF), wave-length (WL) features extracted after denoising were decomposed into a synergy matrix representing the degrees of freedom (DoFs) of the knee joint and an activation coefficient matrix which was closely related to knee joint angles. Activation coefficients were input into the GRNN model based on the golden-section search to calculate the corresponding output angles. In addition, a user graphic interface based on the Java platform was designed to display the dynamic sEMG data and the predicted knee joint angles in real time.

II. Methods

A flowchart of the proposed algorithm is shown in Fig. 1. Data of sEMG signals and knee angle trajectories were divided into the training set and the testing set by a ratio of 3: 1. The wavelet transform threshold method was used for sEMG signals denoising and an overlapping time window was used for feature extraction. Subsequently, the obtained WL features were decomposed by NMF to obtain a synergy matrix and a corresponding activation coefficient matrix. The training data were used to find the appropriate radial basis function (RBF) smoothing parameters based on the 3-fold cross-validation and golden-section search algorithm, so as to construct the GRNN model. Finally, the constructed GRNN model was used to map activation coefficients of the testing set to obtain the predicted results.

A. Muscle Synergy Theory

The former Soviet biologist Bernstein proposed the muscle synergy theory [12] which defined a control unit composed of a number of DoFs as "muscle synergy". Specifically, CNS issues different activation commands to synergies to complete different basic movements, and different limb movements are composed of numbers of basic movements. So the quantification and analysis of the muscle synergies and activation instructions can be helpful to construct the model of human motion.

At present, one of the most common applications of muscle synergy theory in quantitative analysis could be obtaining synergies and corresponding activation coefficients based on the decomposition of sEMG signals. Based on muscle synergy analysis, the muscle activation level can be expressed as a linear combination of numbers of synergies and their corresponding activation sequences:

$$M_{N\times T} = W_{N\times K} \times H_{K\times T} \,. \tag{1}$$

Where $M_{N\times T}$ represents the N-channel muscle activation level matrix whose sampling time is T. $W_{N\times K}$ is the synergy matrix of K synergies, and $H_{K\times T}$ is the activation coefficient matrix corresponding to $W_{N\times K}$. Generally, time-domain features $f(S)$ of the sEMG signals S are approximately linearly correlated with M, so (1) can be approximated as (2).

$$f(S) \approx M = W \times H \tag{2}$$

B. Feature Extraction and Selection

The wavelet transform threshold method was used for denoising. It is suitable for nonstationary and nonlinear sEMG signals, which can keep enough details, and the calculation cost is relatively low.

WL is a reasonable choice for feature extraction, considering that time-domain features are approximately taken as the muscle activation level, knee joint angles are closely associated with the sEMG amplitude, and WL reflects the amplitude, frequency and duration of signals to a certain extent.

For a time window with N sampling points, WL features are calculated as shown in (3).

$$\mathrm{WL} = \sum_{i=1}^{N-1} \left| x_i - x_{i+1} \right| \tag{3}$$

Nonstationary sEMG signals can be approximately regarded as stationary in each analysis window. In consideration of the sampling frequency, an overlapped windowing analysis with a window size of 200 and a sliding step of 20 were adopted.

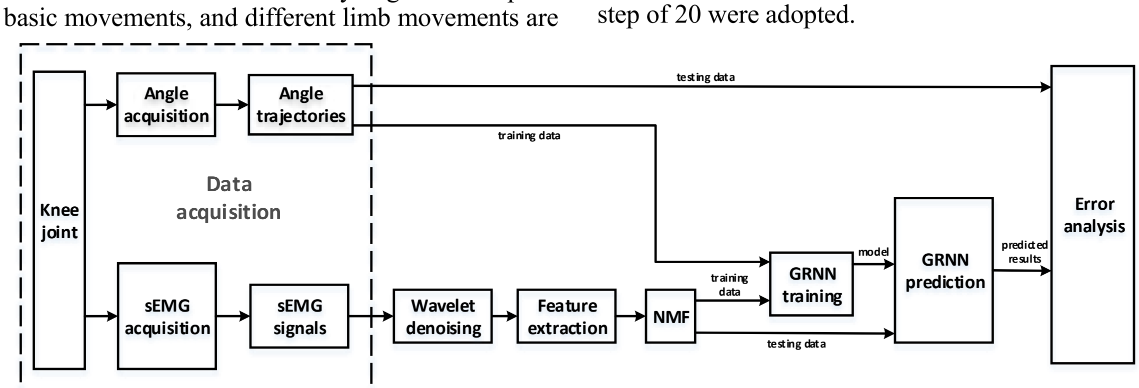

Figure 1. Flowchart of the proposed algorithm.

C. Nonnegative Matrix Factorization

Compared with other blind source separation methods, the results of NMF are nonnegative, which is well coincident with the physiological significance of synergies and activation coefficients. Therefore, NMF is widely used in muscle synergy analysis.

The NMF problem is described as follows: for a given nonnegative matrix $V \in R_+^{n\times m}$, two nonnegative matrices $W \in R_+^{n\times k}$ and $H \in R_+^{k\times m}$ should be found so that $V \approx W \times H$ is satisfied. NMF issues can be expressed in a standard form:

$$\min\|E\|_F = \min\|V - WH\|_F . \tag{4}$$

Where $\|\bullet\|_F$ represents the Frobenius norm and E is the error in factorization.

D. D. Lee and H. S. Seung [13] proved the convergence of NMF and deduced that if E obeyed Gaussian distribution and the variance was equal everywhere, then W and H was updated by the gradient descent method. The final iteration rules were shown as follows.

$$W_{i,k} \leftarrow W_{i,k} \cdot \frac{\left(VH^T\right)_{i,k}}{\left(WHH^T\right)_{i,k}} \tag{5}$$

$$H_{k,j} \leftarrow H_{k,j} \cdot \frac{\left(W^T V\right)_{k,j}}{\left(W^T WH\right)_{k,j}} \tag{6}$$

S. Muceli et al. [14] researched the relationship between the number of synergies and the single-joint movements. The results show that only one synergy cannot describe single-joint movements, however two synergies are sufficient for the description. So the synergy matrix in this research should contain two columns representing the two synergies of the knee joint, and the activation coefficient matrix should contain two rows.

D. Generalized Regression Neural Network Based on Golden-section Search

The sequence of activation coefficients does not exactly correspond to knee joint angles. It is necessary to complete the mapping between activation coefficients and knee joint angle trajectories. GRNN is one of the excellent solutions to this problem.

GRNN is a special RBF neural network with a radial basis network layer and a special linear network layer, which has a good local approximation property and is commonly used in function approximation. The threshold of the radial basis network layer b is affected by the RBF smoothing parameter *spread*, as shown in (7).

$$b = \frac{\left[-\ln 0.5\right]^{\frac{1}{2}}}{spread} \tag{7}$$

The output of radial basis network layer a is shown as (8). Where $\|\bullet\|$ represents Euclidean distance.

$$a = radbas(\|W - p\| \cdot b) \tag{8}$$

The *spread* is the only tunable parameter that determines the performance of the network, so how to choose *spread* is important. In this research, golden-section search was used to optimize the *spread* in the range of [0.09, 0.15].

The coefficient of determination R^2 was chosen as the numerical criterion of errors. It can be used to determine the degree of fit. The expression is shown as (9). Where $\hat{y}_i$ is the estimation of y_i, $\bar{y}$ is the mean of true values.

$$R^2 = \frac{\sum_i \left(\hat{y}_i - \bar{y}\right)^2}{\sum_i \left(y_i - \bar{y}\right)^2} \tag{9}$$

To guarantee the prediction ability and generalization ability, the 3-fold cross validation was applied in the construction of GRNN model. Golden-section search was used to optimize the *spread* in each cross validation. The *spread*, the input and the output in the cross validation, which attained the best performance, were chosen as the optimal parameter and the final training data.

III. Experimental Setup

To improve the quality of the acquired sEMG data, it is necessary to choose reasonable muscle tissues. Biceps femoris, rectus femoris, vastus lateralis and vastus medialis were chosen as sEMG sources. A Biometrics' DataLOG data acquisition instrument was applied in this experiment. The electrode pads were placed at the venter of the muscle tissues, and parallel to the muscle spindles. The reference electrode was placed at the elbow joint, where the number of muscle fibers is relatively small.

In this research, a knee joint angle was defined as the included angle between the extension midline of the thigh and the midline of shank while subjects sat upright, which is shown in Fig. 2. In the experiment, two pieces of MPU6050 (Integrated 6-axis motion processing module) were fixed on the midline of thigh surface and the midline of shank surface near the knee, so that the flexion and extension movements of the knee joint would make the included angle between the two sensors change. C51 microcontroller was used as an interface to transmit data to a host computer for the angle fusion, and finally obtain knee joint angles.

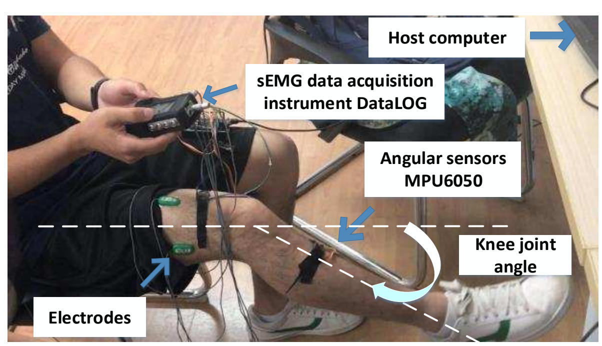

Figure 2. A Subject is conducting the experiment.

Subjects were instructed to do the knee extension movement from the initial place, where the knee joint angle is about 90°, to a certain place, and then do the flexion movement back to the initial place. Knee joint angles ranged from 0°, where the midline of thigh surface was parallel to the midline of shank surface, to 90° throughout the process. This whole process was defined as one "movement". Each experiment was composed of two groups of three continuous "movements" and a one-minute rest interval. According to this experimental method, four healthy male subjects between the ages of 20 to 24 were selected to carry out the experiment. Since the weight of the human gait in the vertical plane is much larger than the other two planes [15], the knee movements discussed in this research are only for the vertical plane, and subjects should pay attention to ensuring that lower limb movements are mainly conducted in the vector plane. The experimental setup is shown in Fig. 2.

IV. Results and Discussion

As shown in Fig. 3 and Fig. 4, after NMF processing, WL features are approximately decomposed into a 4×2 synergy matrix and a 2-row activation coefficient matrix whose column number is same as the number of window analysis.

Each column in the synergy matrix presents one synergy related to knee joint movements, and every channel in different synergies has a different contribution, in other words, the four muscles related to the knee joint movements have different contributions to the two synergies just as the Fig. 3 shown. Moreover, as abstract structure units of human body, synergies of different subjects can be different in component. As shown in Fig. 4, each synergy corresponds to an activation coefficient sequence. According to the muscle synergy analysis, activation coefficients are considered as the activation commands issued by CNS, which are strongly correlated with knee joint angles. Therefore, to complete the prediction, it is necessary to find out the mapping relation between activation coefficients and knee joint angles.

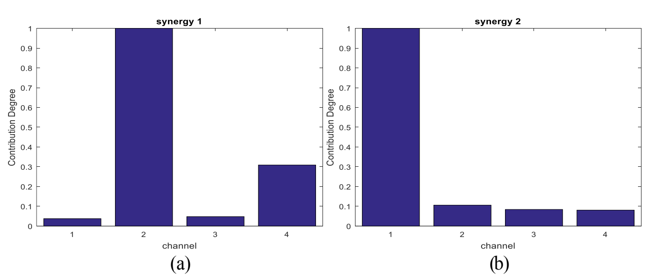

Figure 3. Two muscle synergies of the knee extracted from time-domain features by NMF, (a) synergy 1 (b) synergy 2.

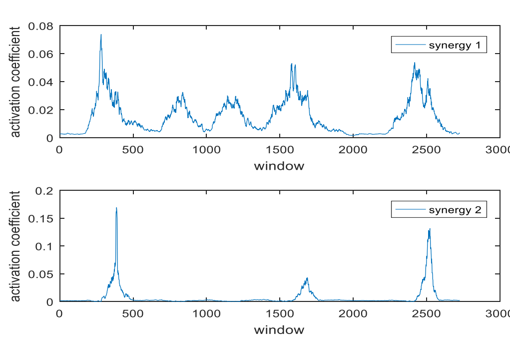

Figure 4. Activation coefficients corresponding to muscle synergies.

By using trained GRNN models based on golden-section search, the predicted results of four subjects and actual reference angles are shown in Fig. 5, and the corresponding average coefficients of determination are shown in TABLE I.

According to the Fig. 5 and TABLE I, it can be seen that the GRNN activation model for each subject has a good prediction effect on knee joint angles, with a mean coefficient of determination of 0.933. As a preliminary study, the number of subjects is relatively small. In the future research, the number of subjects will increase to further verify the reliability of the proposed algorithm.

As for the results, the errors mainly come from the following aspects:

- Throughout the experiment, the subject's muscle state was changing all the time. For example, muscle fatigues are aggravating, so the raw data will be affected, which means that one joint angle may correspond to different muscle activation level;
- NMF is an approximate decomposition, which cannot contain all the effective information of WL features. Therefore, it is somewhat definite that there are errors while the approximate decomposition results are applied to the prediction model;
- In order to ensure the sufficient generalization ability of the GRNN model, which is an important judgment criteria of regression models, the initial range of parameter optimization is relatively large. Although the performance of single data set is reduced, the overall robustness and generalization ability are improved;
- Neural network is a purely mathematical model, its accuracies entirely depend on the training data. Once there is a great difference between the training data and test data, the prediction accuracies will be reduced.

A visual interactive interface based on Java platform is showed in Fig. 6. It can display the dynamic sEMG signals in real-time, call the model for angle prediction and feed the results back to Java platform for display.

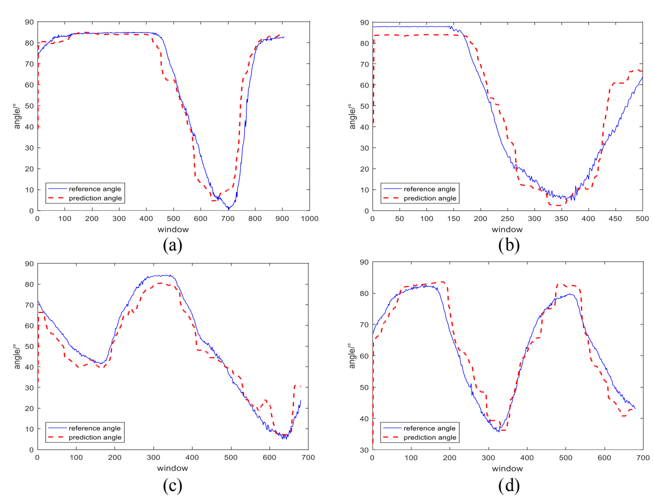

Figure 5. Prediction results of four subjects. Sub-figure (a), (b), (c), (d) are the prediction results of Subject A, B, C, D respectively.

TABLE I. SUBJECTS' RESPECTIVE AVERAGE COEFFICIENTS OF DETERMINATION

Subjects	*coefficient of determination* R^2	*Mean*
A	0.9289	
B	0.9370	0.9327
C	0.9431	
D	0.9218	

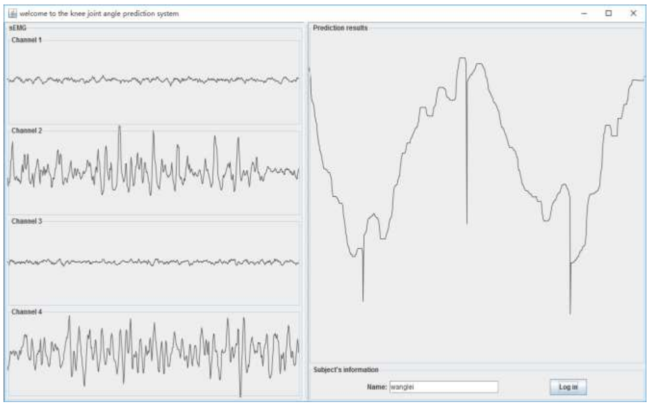

Figure 6. User graphic interface based on the Java platform. The left four frames are used for the display of dynamic waveform of four-channel sEMG signals, while the top-right area is used for the display of the prediction angle trajectories, the bottom-right part is the user's login area.

V. CONCLUSION

In this paper, a knee joint angle prediction system based on muscle synergy theory and GRNN was proposed. Four healthy male subjects between the ages of 20 to 24 carried out the experiment, in which subjects did knee extension and flexion movements six times with one-minute rest interval. The acquired data were denoised by the wavelet transform threshold method. To obtain the activation commands issued by CNS, NMF was applied to extract knee joint synergies and activation coefficients from wave-length features of sEMG signals, and a GRNN model based on golden-section search was constructed for activation coefficients mapping to knee joint angles. The experimental results show that the grand average coefficient of determination is 0.933. In addition, a graphical user interface based on Java platform was designed to validate the proposed method and realize a friendly HMI. Properly predicted angles can be used to achieve continuous, smooth control on the robot platform, enable the robot to perform human-like smooth movements rather than discrete prescribed ones, which has important research significance in rehabilitation aids, military, remote operations and so on. Furthermore, a linear combination of one set of muscle synergies can describe multi-DoF movements of single joint or multiple joints. With an improvement, the proposed method can realize the prediction for more complex movements. This is the topic of future research.

ACKNOWLEDGMENT

All authors in this research would like to thank Lei Wang, Jifa Cai, Wenhao Zheng and Weifeng Wu for their involvements in experiment and data records.

REFERENCES

[1] S. Amsüss, P.M. Goebel, N. Jiang, B. Graimann, L. Paredes and D. Farina, "Self-correcting pattern recognition system of surface EMG signals for upper limb prosthesis control," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 4, pp. 1167-1176, Apr. 2014.

[2] T. Matsubara and J. Morimoto, "Bilinear Modeling of EMG Signals to Extract User-Independent Features for Multiuser Myoelectric Interface," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 8, pp. 2205-2213, Aug. 2013.

[3] J. Liu and P. Zhou, "A novel myoelectric pattern recognition strategy for hand function restoration after incomplete cervical spinal cord injury," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 1, pp. 96-103, Jan. 2013.

[4] J. Han, Q. Ding, A. Xiong and X. Zhao, "A state-space EMG model for the estimation of continuous joint movements," *IEEE Trans. Ind. Electron.*, vol. 62, no. 7, pp. 4267-4275, July 2015.

[5] E.E. Cavallaro, J. Rosen, J.C. Perry, and S. Burns, "Real-Time Myoprocessors for a Neural Controlled Powered Exoskeleton Arm," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 11, pp. 2387-2396, Nov. 2006.

[6] M. Pang, S. Guo, Q. Huang, H. Ishihara, H. Hirata, "Electromyography -Based Quantitative Representation Method for Upper-Limb Elbow Joint Angle in Sagittal Plane," *J. Med. Bio. Eng.*, vol. 35, no. 2, pp. 165-177, Apr. 2015.

[7] S. Zhang, S. Guo, B. Gao, Q. Huang, M. Pang, H. Hirata, H. Ishihara, "Muscle Strength Assessment System Using sEMG-Based Force Prediction Method for Wrist Joint," *J. Med. Bio. Eng.*, vol. 36, no. 1, pp. 121-131, Feb. 2016.

[8] G. Cheron, F. Leurs, A. Bengoetxea, J.P. Draye, M. Destrée and B. Dan, "A dynamic recurrent neural network for multiple muscles electromyographic mapping to elevation angles of the lower limb in human locomotion," *J. Neurosci. Methods*, vol. 129, no. 2, pp. 95-104, Oct. 2003.

[9] F. Zhang, P. Li, Z. Hou, Z. Lu, Y. Chen, Q. Li and M. Tan, "sEMG-based continuous estimation of joint angles of human legs by using BP neural networks," *Neurocomputing*, vol. 78, no. 1, pp. 139-148, 2012.

[10] L. Tong, F. Zhang, Z. Hou, W. Wang, L. Peng, "BP-AR-based human joint angle estimation using multi-channel sEMG," *Int. J. Robot. Autom.*, vol. 30, no. 3, pp. 227-237, 2015.

[11] R. Raj and K. Sivanandan, "Elbow joint angle and elbow movement velocity estimation using NARX-multiple layer perceptron neural network model with surface EMG time domain parameters," *J. Back Musculoskelet. Rehabil.*, vol. 30, no. 3, pp. 515-525, May 2017.

[12] D.P. Black, M.A. Riley and C.K. McCord, "Synergies in intra- and interpersonal interlimb rhythmic coordination," *Motor Control*, vol. 11, no. 4, pp. 348-373, 2007.

[13] D.D. Lee, H.S. Seung, "Algorithms for Nonnegative Matrix Factorization," presented at the 2000 Int. Conf. Neural Inf. Process. Syst., Denver, CO.

[14] S. Muceli, A.T. Boye, A. D'Avella and D. Farina, "Identifying representative synergy matrices for describing muscular activation patterns during multidirectional reaching in the horizontal plane," *J. Neurophysiol.*, vol. 103, no. 3, pp. 1532-1542, Jan. 2010.

[15] N. Yang, "Coordination Analysis and Parametric Description of Human Movements," Ph.D. dissertation, Dept. of Precision Instruments and Mechanology, Tsinghua Univ., Beijing, China, 2001.