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Pattern Recognition of Continuous Elbow Joint Movements Using Bispectrum-based sEMG

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***Abstract* – Due to the fact the sEMG can directly reflect the human neuromuscular activity, motion pattern recognition with surface electromyographic signal (sEMG) have been used to achieve human joint motions tracking in the rehabilitation medical engineering filed. However, the sEMG signal is non-Gaussian signal and the non-Gaussian component contains rich information of sEMG signal. Time-domain and frequency-domain features based lower order statistics joint sEMG commonly used cannot characterize the non-Gaussian information of signal. In this paper, we utilized the bispectrum estimators containing non-Gaussian information and the integral of bispectrum slice combined with time-domain features is extracted as features to recognize the elbow motion intention hidden in the filtered sEMG signals from the biceps muscle with good performance compared to other mothods in terms of classification accuracy.**

***Index Terms - rehabilitation training. surface EMG. bispectrum feature. elbow movements*.**

I. INTRODUCTION

Hemiplegia is usually caused by stroke and other brain diseases, which is likely to cause partial loss of most patients' Activities of Daily Living [1], [2]. Upper-limb function is the most important for many ADL. Improving upper-limb ability after a brain lesion requires early and intensive therapy [3]. The medical rehabilitation robot is mainly used to restore the function of the limb motor system in medical practice [4]. Recently, surface electromyographic (sEMG) as the control source of rehabilitation system to achieve the friendly human-machine interaction has been widely applied in motion recognition to explore the movement intention of patients because it can reflect the neuromuscular activities of muscles [5]. sEMG-based motion pattern recognition process commonly includes: sEMG acquisition, pre-processing, feature extraction and pattern classification. Feature extraction and pattern classification are main and important processes during the recognition. Precise feature extraction can be used to acquire more available information from the input raw sEMG signals with the purpose of realizing the precise motion classification.

The commonly used feature extraction methods are mainly separated into three types: time domain, frequency domain and time-frequency domain [6]. The methods of time domain mainly include Integrated EMG (IEMG), Mean Absolute Value (MAV) and so on [7]. The methods of frequency domain mainly include Auto-Regressive coefficients (AR), frequency Median (FMD) and so on [8]. The methods of time-frequency domain were developed based on that in frequency domain and include Wavelet Transform (WT) and Wavelet Packet Transform (WPT) [9]. The typical methods of feature classification are Artificial Neural Network (ANN) [10] which is good at dealing with nonlinear problems, Bayesian classifier (BC), Fuzzy Logic Classifier (FLC) and Support Vector Machines (SVM) [11].

As the complex and non-stationary properties sEMG may be easily influenced by physiological properties and recoding tool. sEMG is non-Gaussian amplitude distribution and the non-Gaussian component contains abundant information of sEMG signal. However, the feature extraction method based on first-order and second-order statistics cannot satisfy the processing requirement for sEMG to obtain non-Gaussian information and the combination of higher-order statistics and other statistics as features is rarely reported. Some methods based on higher-order spectrum analysis were proposed to the application for signal feature extraction. In [12], the researchers propose a discriminant bispectrum (DBS) feature extraction method to recognize sEMG signal for prosthetic control. The six channels' sEMG signals are acquired and the DBS has better performance than other features for identifying the hand motion patterns. the bispectrum features are extracted from four sEMG signal channels used for myoelectric control [13]. From above studies, bispectrum analysis, a second-order Fourier transform of third-order cumulant, is a commonly used higher-order spectrum analysis tool [14].

In our previous research, Zhibin Song [15] proposed an improved weighted peaks method to process the filtered sEMG signals from the biceps muscle and adapted linear fitting method to obtain the elbow motion in sagittal plane. Zhenyu Wang [16] utilized the multi-scale entropy and moving-window method to reveal the elbow motion information hidden in the filtered sEMG signals from the biceps muscle. Xuan Song [17] utilized a novel method Ensemble Empirical Mode Decomposition (EEMD) to process the raw sEMG signals and the continuous posture of elbow flexion and extension were recognized based on this method. However, the non-Gaussian of sEMG signal was not considered.

In this paper, we will acquire the sEMG of the patient's healthy upper limb to guide the rehabilitation robot assisting the hemiplegic upper limb executing rehabilitation training. Based on the previous studies and non-Gaussian of sEMG signal, we mainly focus on: one part is to extract the bispectrum feature of sEMG from upper limb movements and construct features space; the second part is motion pattern recognition. Features space is constructed combined the bispectrum feature and time-domain feature of sEMG signal from the biceps muscle. Finally, the effectiveness of this feature extraction method is verified and recognized by motion classification experiment using ANN, and the output from the neural network is used as a command to drive the upper limb exoskeleton rehabilitation device to implement the bilateral rehabilitation

II. METHODOLOGY

Bilateral rehabilitation is a feasible way of rehabilitation training that use the patients' healthy upper limb to guide the rehabilitation robot assisting the hemiplegic upper limb executing rehabilitation training, and the motion pattern racking on the health side of the upper limb is an important aspect for achieving rehabilitation robot control. As Fig.1 shown, the system includes nearly five sections: data acquisition, data preprocessing, feature extraction, motion recognition and bilateral rehabilitation.

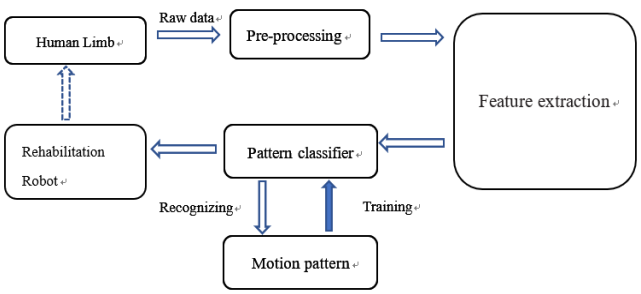


Fig. 1. Flow block diagram of the whole bilateral rehabilitation system.

A. sEMG signal acquisition and experiments

Although elbow motion may involve biceps muscle, triceps and other muscles, it is likely to complete the motion recognition with one channel sEMG signal from the biceps muscle. Figure 2 shows the raw sEMG signal acquisition sensor and Figure 3 presents the upper limb rehabilitative robot.

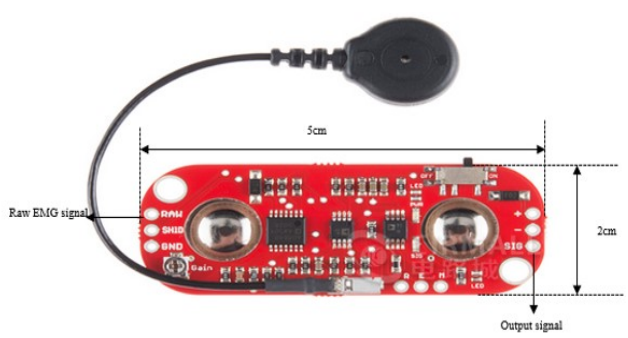


Fig. 2. Muscle sensor for acquiring the sEMG signal.

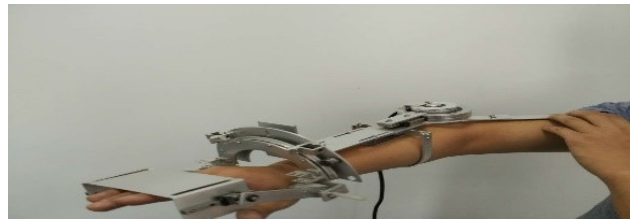
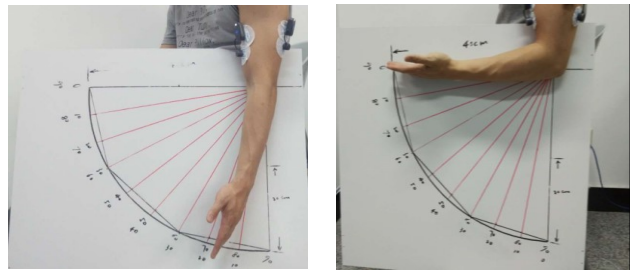


Fig. 3. Upper limb rehabilitative robot device.



(a) (b)

Fig. 4. Elbow joint motion: (a) elbow flexion 0° (initial state); (b) elbow flexion 90° (terminate state).

The raw sEMG signals were acquired using the bipolar surface electrodes with 12mm in diameter, located 18mm apart, and the sampling rate is 1000Hz. As Fig. 4 shown, the subject was required to take 30° as a step, and we collected sEMG signals from 0° to 90° of elbow flexion from brachial muscles. The muscles of participants without neurological abnormalities or muscle disease were not fatigued during the experiment. The participants should sit on the chair and their right hand relaxed and droop, whose body was relaxed before performing the task and then and finish all the movements with the right power. In order to avoid the interference of extra EMG signals generated by the upper arm movement, the arm cannot be moved before muscle sensor collects the EMG signal of the biceps muscle. The sEMG signal of each subject need to be collected 20 stages; 4 different angles are involved in each stage; each angle is collected for about 5s at a stage. The acquisition data of the first 10 stages are the training sample set, and the data of the remaining 10 stages are the test sample set. Each. In order to exclude muscle fatigue, there are 20s to rest at each acquisition interval. Fig. 5 shows the recorded raw sEMG signal of elbow flexion from a subject's biceps muscle.

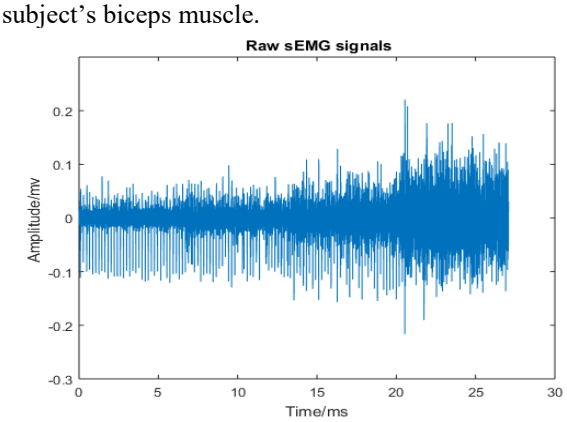


Fig. 5. Raw sEMG signal from biceps muscle.

B. Non-Gaussian examination

In this section, the non-Gaussian characteristic of the sEMG signal will be verified. Skewness and kurtosis are commonly used to measure the signal Gaussian characteristic in the engineering field [18]. The skewness is the third-order moments of signal and the kurtosis is the fourth-order moments of signal. Kurtosis indicates the approximate state of the signal probability density distribution close to the center. The signal with kurtosis equal to 3 is Gaussian signal, and the signal with kurtosis not equal to 3 is non-Gaussian signal. For non-Gaussian signal, the signal with kurtosis greater than 3 is super-Gaussian signal and the signal with kurtosis less than 3 is sub-Gaussian signal. Kurtosis is selected to study the non-Gaussian characteristic of sEMG signal. The kurtosis of a distribution is defined as formula (1) [19].

$$K=\frac{E\left[X-E\left(X\right)\right]^4}{\left\{E\left[X-E\left(X\right)\right]^2\right\}^2} \tag{1}$$

where $E\left(X\right)$ refers to the mean of sample X.

C. Bispectrum feature extraction

The bispectrum is defined as formula (2), which is a Fourier transform of third-order cumulant.

$$B_x\left(\omega_1,\omega_2\right)=S_{3,x}=\sum_{\tau_1}\sum_{\tau_2}C_{3,x}\left(\tau_1,\tau_2\right)*e^{(-\mathrm{j}(\omega_1\tau_1+\omega_2\tau_2))} \tag{2}$$

where $\left|\omega_1\right|\le\pi;\left|\omega_2\right|\le\pi;\left|\omega_1+\omega_2\right|\le\pi$ and $C_{3,x}\left(\tau_1,\tau_2\right)$ refers to the third-order cumulant of $\{X_k\}$ and $B_x\left(\omega_1,\omega_2\right)$ refers to bispectrum.

1) Data segmentation: Due to the real-time requirement of EMG control, the response time of the system should be less than 300ms. The interception length of signal data is directly proportional to the signal processing time. However, the shorter data length will cause the increase of the characteristic deviation and variance, such resulting in the decrease of classification rate. The previous research on the classification of electromyography shows that the delay produced by the signal length of 200ms-300ms is acceptable, and the recognition rate of action will not decrease significantly. In this paper, we use 256ms (256 point) analysis window to intercept data, and the sliding increment of the window is 256ms. Therefore, there will be 195*4 train samples to train the neural network.

2) Bispectrum estimation: Bispectrum retains many non-Gaussian information of sEMG signal with periodicity and symmetry characteristics. However, signal is always finite length so that bispectrum cannot be accurately calculated in practical engineering applications. In this paper, the direct method which is available for real-time analysis is selected to estimate the bispectrum matrix of the sEMG signal. The estimation process was as follows:

(1) Divide the sEMG signal into K segments with M data points in each segment and 50% overlap between segments.
(2) Remove the mean value of each segment.
(3) Make the Fast Fourier Transform for each segment.
(4) Estimate the bispectrum on the result of Fast Fourier Transform of each data segment as formula (3).

$$\hat{B}^i_{xx}\left(\omega_1,\omega_2\right)=M^2\,\hat{X}^i\left(\omega_1\right)\hat{X}^i\left(\omega_2\right)\hat{X}^{i*}\left(\omega_1+\omega_2\right) \tag{3}$$

where $\hat{X}^i\left(\omega\right)$ refers to Fourier Transform of the i th segment, and i =1, 2, . . ., k, X^{i*} refers to conjugate transpose.

(5) Calculate the statistical average of the bispectrum estimated results through formula (4) and get the bispectrum matrix of the whole samples.

$$\hat{B}_{xx}\left(\omega_1,\omega_2\right)=\frac{1}{K}\sum_{i=1}^{K}\hat{B}^i_{xx}\left(\omega_1,\omega_2\right) \tag{4}$$

where $\hat{B}_{xx}\left(\omega_1,\omega_2\right)$ refers to the bispectrum of the i th data segment.

3) Bispectrum slice: Bispectrum matrix is a matrix of 128 by 128 according to the Fourier transform length is 128, which is not suitable to use as input features of the whole bispectrum matrix directly due to its high dimensionality. One-dimension bispectrum slice [20] is calculated of the bispectrum matrix to extract feature available. Based on the symmetry of bispectrum, the distributions of corresponding slices of horizontal and vertical direction were same. In our research, horizontal slice was selected for feature extraction. In formula (5), by setting constant c at different values, different levels of bispectrum slices will be acquired.

$$B_x\left(\omega_1,c\right)=X\left(\omega_1\right)X\left(c\right)X^*\left(\omega_1+c\right)\qquad\left(\left|c\right|\le\pi\right) \tag{5}$$

where set $c = c_1,c_2,\ldots$ (n is the row number of the bispectrum matrix). And then, the bispectrum feature will be extracted by calculating the integration of each slice's amplitude with log compression transform of the integration through formula (6). Finally, there were 128 bispectrum features for one sample.

$$Bis\_c=\log\left(\int_{-\infty}^{\infty}\left|B_x\left(\omega_1,\mathrm{c}\right)\right|d\omega_1\right) \tag{6}$$

where Bis_c is the bispectrum axial integral features.

4) Time-domain features and features space: horizontal slice generates a high-dimension feature vector involves 128 features of data sample, and the amount of computation will be larger in the process of classification. While extracting features from fewer slices, some information of bispectrum will be lost. In our research, the principal component analysis (PCA) [21] method is used to select most effective feature vectors that retain main information from bispectrum slice feature to reduce the feature dimension such forming $PCABis$ features matrix. In order to increase the separability between antagonistic movements and improve the pattern

recognition accuracy of the whole movement, the time-domain feature and bispectrum feature will be combined to construct the multi-domain joint feature space. The sample is divided into two sections, and the integral of each section is calculated in formula (7).

$$\begin{cases} tEMGa = \int_0^{N/2} |X(t)| dt \\ tEMGb = \int_{N/2}^{N} |X(t)| dt \end{cases} \tag{7}$$

where $tEMGa$ refers to the absolute integral sEMG value of the first half signal, and $tEMGb$ is the absolute integral sEMG value of the second half signal, N refers to the point number of a sample and $X(t)$ is the amplitude of the sEMG signal at time t. Combine the *PCABis* and Time-domain features of the sEMG, the joint feature space $Bis\&\mathrm{T}$ is constructed as shown in formula (8).

$$Bis\&\mathrm{T} = \left[tEMGa \quad tEMGb \quad PCABis \right] \tag{8}$$

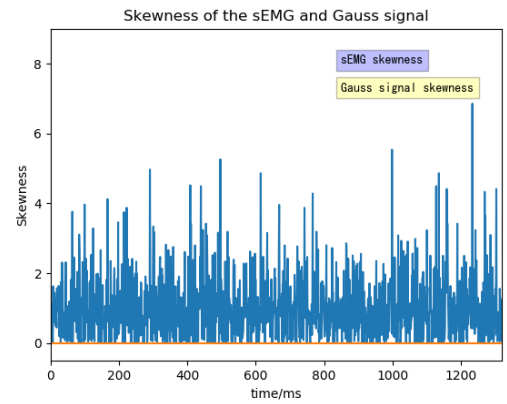
D. Nonlinear map from the sEMG to motion

In this experiment, the subject was required to perform the elbow flexion and extension with his upper arm relaxed in the sagittal plane at a low and constant speed. We adapted a three-layer Artificial Neural Network (ANN) [22] method to realize the classification of elbow flexion motion states (involving 0°, 30°, 60°, 90°). We used the features of features space $Bis\&\mathrm{T}$ as the input layer. To get a better modelling of the complex activities of nervous system during elbow motion, we utilized 10 hidden neuron nodes in the hidden layer. In the output layer we simplified the elbow flexion motion to be 4 states (0°, 30°, 60°, 90°).

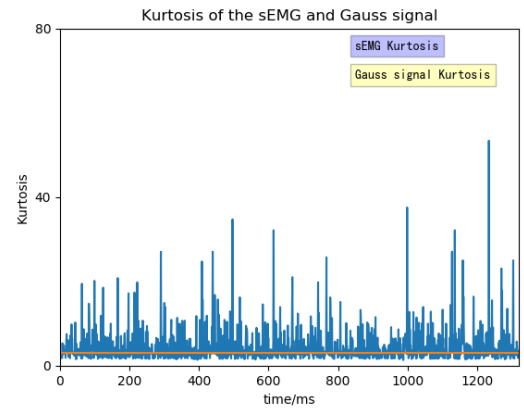
III. Experiments And Results

Three healthy subjects were invited to implement the experiment to verify the robustness and efficiency of $Bis\&\mathrm{T}$ features applied in the motion recognition. They needed to perform elbow motion slowly on the sagittal plane with upper arm relaxed. Although sEMG is non-stationary, it is likely to be stationary within a limited data length [23]. According to [11], the data is segmented into sliding windows of 256 samples with overlapping of 128 samples due to fact the length of EMG data should not exceed 300ms. In our research, the number of samples in each signal segment is set to 64 points.

The kurtosis value of the sEMG signal acquainted from each subject in each angle respectively, when performing elbow flexion and extension. As figure 6 shown, each data point represents the skewness or kurtosis of a channel number when performing elbow flexion and extension at all angle. Almost all sample skewness is greater than 0, and kurtosis is greater than 3.



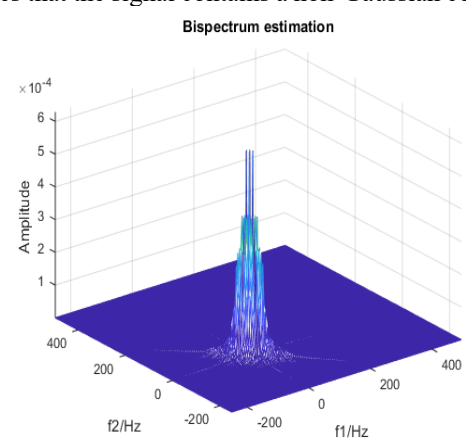
(a)



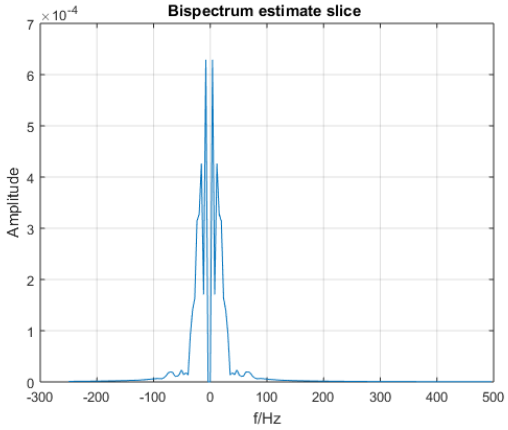
(b)

Fig. 6. The skewness and kurtosis for sEMG and Guass signal. Blue line is the skewness and kurtosis of sEMG; yellow line is the skewness and kurtosis of Guass signal: (a) the skewness of sEMG and Guass signal; (b) the kurtosis of sEMG and Guass signal.

Because the sEMG signal is non-Gaussian signal, the bispectrum of the sEMG signal was estimated. Figure 7 shows the bispectrum distribution and one-dimensional slice distribution of bispectrum of the sEMG signal when subject perform elbow extension. Bispectrum has two horizontal axes, which are the angular frequency. The nonzero value indicates that the signal contains a non-Gaussian component.



(a)



(b)

Fig. 7. (a) The bispectrum distribution of sEMG signal from biceps muscle; (b) one-dimensional slice distribution of bispectrum.

To make it convincible, we analyzed 195*4 predicted samples for each subject, classification accuracies were calculated in motion states 0°, 30°, 60°, 90° by setting a threshold to measure the displacement of the predicted motion and the motion record. Then we got the average accuracies to evaluate the performance of the motion recognition. Compared with average classification accuracy based on Time-Frequency feature, Table I shows the results of average classification accuracy between *Bis* & T features by ANN classifier of all subjects. The data are acquired by muscle sensor shown in Fig. 2.

TABLE I
AVERAGE CLASSIFICATION ACCURACY

Subject	Classification Accuracy			
	Bis & T feature		Time-Frequency feature	
	Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy
A	95.3%	80.2%	92.1%	78.2%
B	96.8%	74.6%	96.6%	73.8%

As shown in Table I, the classification accuracy based on Time-Frequency feature and *Bis* & T features are not very well, and the training set may have been overfitted. The reasons may include: the quality of the data acquired by Muscle Sensor may be so poor that the classification accuracy is affected; only one channel signal is acquired which implies only one active muscle is recruited in this paper; Training sample sets may be inadequate. The average classification accuracy based on *Bis* & T is about 77% and that based on Time-Frequency feature is about 75%. However, for the same subject, the classification accuracy of *Bis* & T feature is higher than that of Time-Frequency feature.

IV. CONCLUSIONS

In this paper, we concentrated on the recognition of continuous elbow flexion and extension motion on sagittal plane with one channel surface EMG from the bieceps muscle. The sEMG was super-Gaussian signal with non-Gaussian information, and the non-Gaussian information contained in the signal was expected to increase pattern characteristic capabilities. Therefore, the feature extraction method on non-Gaussian information was studied. bispectrum as the third-order statistics involves rich non-Gaussian information. Therefore, the feature of the bispectrum integration of sEMG signal is extracted. And then the bispectrum-based feature with low dimension was calculated by PCA. In order to realize promote the separability between antagonistic movements and improve the accuracy of recognition, the absolute integral sEMG values were also calculated. After that, the feature space *Bis* & T combined bispectrum integration and time-domain feature was constructed as the input vector of the three-layer BP network to map the processed sEMG to elbow motion. Finally, the performance of *Bis* & T features was verified by the output of the Artificial Neural Network. The future study will focus on bispectrum-based sEMG features exraction of Multi-degree-of-freedom and compound action recognition to improve the classification accuracy and enhance real-time application.

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REFERENCES

[1] G. Prange, M. Jannink, C. Groothuis-Oudshoorn, H. Hermens and M. IJzerman "Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke," *Rehabil Res Dev*, vol. 43, no. 2, pp. 161–183, 2006.

[2] S. Zhang, Shu. Guo, Mu. Pang, B. Gao, and P. Guo, "Mechanical Design and Control Method for SEA and VSA-based Exoskeleton Devices for Elbow Joint Rehabilitation," *Neuroscience and Biomedical Engineering*, vol. 2, no. 3, pp. 142-147, 2015.

[3] S. Zhang, S. Guo, B. Gao, H. Hirata, and H. Ishihara, "Design of a Novel Telerehabilitation System with a Force-Sensing Mechanism," *Sensors*, vol. 15, no. 5, pp. 11511-11527, 2015.

[4] B. Gao, H. Ma, S. Guo, H. Xu, and S. Yang, "Design and Evaluation of a 3-degree-of-freedom Upper Limb Rehabilitation Exoskeleton Robot," in proceeding of *2017 IEEE International Conference on Mechatronics and Automation, August 6-9, Takamatsu, Japan*. pp.938-942, 2017.

[5] S. Guo, M. Pang, B. Gao, H. Hirata, and H. Ishihara, "Comparison of sEMG-Based Feature Extraction and Motion Classification Methods for Upper-Limb Movement," *Sensors (Basel)*, vol. 15, no. 4, pp. 9022-9038, 2015.

[6] T. Sharma and K. Veer, "EMG classification using wavelet functions to determine muscle contraction," *Journal of Medical Engineering & Technology*, vol. 40, no. 3, pp. 99-105, 2016.

[7] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews in Biomedical Engineering*, vol. 30, no. 4, pp.459-468, 2002.

[8] A. Phinyomark, C. Limsakul, and P. Phukpattaranont. "A novel feature extraction for robust EMG pattern recognition," *Journal of Computing*, vol. 1, no. 1, pp.71–80, 2009.

[9] M. Jiang, R. Wang, J. Wang, and D. Jin, "A Method of Recognizing Finger Motion Using Wavelet Transform of Surface EMG Signal." in Proceeding of *2005 IEEE Engineering in Medicine and Biology*, pp.2672-2674, 2005.

[10] J. Han, Q. Ding, A. Xiong, and X. Zhao. "A State-Space EMG Model for the Estimation of Continuous Joint Movements," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 7, pp. 4267-4275, July, 2015.

[11] G. Saevarsson, J. Sveinsson, and J. Benediktsson, "Wavelet-packet Transformation as a preprocessor of EEG waveforms for classification," in Proceeding of *19th IEEE Annual International Conference on Engineering in Medicine and Biology Society*. pp. 1305–1308, 1997.

[12] X. Chen, X. Zhu, and D. Zhang, "A discriminant bispectrum feature for surface electromyogram signal classification". *Med Eng Phys*, vol. 32, no. 2, pp. 126–135, 2010.

[13] E. Orosco, N. Lopez, and F. Sciascio, "Bispectrum-based features classification for myoelectric control," *Biomedical Signal Processing and Control,* vol. 8, no. 2, pp. 153–168, 2013.

[14] Y. Chen, Y. Zhou, X. Cheng, X. Fan, and Y. Zhang. "Bispectrum-based sEMG multi-domain joint feature extraction for upper limb motion classification," *Mechanical Engineering Science,* vol. 230, no. 2, pp. 248–258, 2016.

[15] Z. Song, Z. Wang, and S. Guo, "SEMG-based Continuous Posture Recognition of Elbow Flexion and Extension in Sagittal Plane," in Proceeding of *2013 IEEE International Conference on Mechatronics and Automation, August 4-7, Takamatsu, Japan*. pp.920-925, 2013.

[16] Z. Wang, S. Guo, B. Gao, and X. Song, "Posture Recognition of Elbow Flexion and Extension Using sEMG Signal Based on Multi-Scale Entropy," in Proceeding of *2014 IEEE International Conference on Mechatronics and Automation, August 3-6, Tianjin, China*. pp.1132-1136, 2014.

[17] Z. Song, Z. Wang, and S. Guo, "Motion Recognition of the Bilateral Upper-limb Rehabilitation using sEMG Based on Ensemble EMD," in Proceeding of *2014 IEEE International Conference on Mechatronics and Automation, August 3-6, Tianjin, China*. pp.1637-1642, 2014.

[18] Y. Jiang, X. Chen, J. Tao, and C. Zhang, "Numerically simulating non-Gaussian random processes with specified PSD, skewness and kurtosis," *Journal of System Simulation*, vol. 18, no. 5, pp. 1127–1130, 2006.

[19] S. Yu and M. Lee, "Bispectral analysis and genetic algorithm for congestive heart failure recognition based on heart rate variability," *Computers in Biology and Medicine,* vol. 42, no. 8, pp. 816–825, 2012.

[20] Y. Zhou, J. Chen, G. Dong W. Xiao, and Z. Wang, "Application of the horizontal slice of cyclic bispectrum in rolling element bearings diagnosis," *Mechanical Systems and Signal Processing*, vol. 26, no. 6, pp. 229–243, 2012.

[21] R. Martis, U. Acharya, and L. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform," *Biomedical Signal Processing and Control*, vol.8, no. 5, pp. 437–448, 2013.

[22] S. Zhang, S. Guo, B. Gao, Q. Huang, M. Pang, H. Hirata, and H. Ishihara, "Muscle Strength Assessment System using sEMG-Based Force prediction Method for Wrist Joint," *Journal of Medical and Biological Engineering*, vol. 36, no. 1, pp. 121-131, 2015.

[23] M. Bilodeau, M. Cincera, A. Arsenault, and D. Gravel. "Normality and stationarity of EMG signals of elbow flexor muscles during ramp and step isometric contractions," *Journal of Electromyography and Kinesiology*, vol. 7, no. 2, pp. 87–96, 1997.