Proceedings of 2019 IEEE
International Conference on Mechatronics and Automation
August 4 - 7, Tianjin, China

A Method of Evaluating Rehabilitation Stage by sEMG Signals for the Upper Limb Rehabilitation Robot

Shuxiang Guo[1,2] and Huimin Cai[1]

[1]*Tianjin Key Laboratory for Control Theory & Applications in Complicated Systems and Biomedical Robot Laboratory*
Tianjin University of Technology
Binshui Xidao Extension 391, Tianjin,China
guoshuxiang@bit.edu.cn; 389935788@qq.com.

Jian Guo[1*]

[2]*Intelligent Mechanical Systems Engineering Department*
Faculty of Engineering
Kagawa University,
Takamatsu, Kagawa, Japan
*corresponding author: jianguo@tjut.edu.cn;

***Abstract* - Stroke can easily lead to nerve injury, which will bring inconvenience in life. Research shows that this kind of injury can be improved by using rehabilitation robots for rehabilitation training. In this paper, a method of evaluating and classifying rehabilitation stages by sEMG signals are proposed, and the feasibility of this method is verified. Firstly, a method to distinguish the impaired side from the healthy side using sEMG signals are proposed, and its accuracy is verified by simulation experiments. Through this experiment, some better feature are chosen to evaluate the muscle strength. sEMG signals of the upper-limb muscles of the patients are denoised and analyzed in time domain and frequency domain. sEMG signals are then obtained into the training set and the test set, using the training set to make the weighed evaluation for the unknown rehabilitation stage and calculate the final classification results. The experiments are carried out and the result verified the feasibility of using sEMG signals to distinguish the rehabilitation stage.**

Index terms – Exoskeleton hand robot ; Rehabilitation Training evaluate ; feature extraction；

I. Introduction

Stroke can easily cause acquired long term disability. When a person is in a stroke, interrupting the supply of blood to the brain increases intracranial pressure and the toxic released by blood cause serious damage to the brain. Depending on the location of the disease, it can lead to various physical impairments, including muscle weakness, loss of sensation and cognitive impairment. These physical impairments can have a huge impact on the quality of life for stroke survivors. Some can't even finish simple actions like eating and walking, and can't live independently. More than half of the stroke survivors' daily lives require the help of others. Although mostly, tissue damage can not be completely cured , it turns out that using brain remodeling ability with stroke rehabilitation can restore some body functions[1]. Assessment of costs associated with clinical neurological rehabilitation, and the ability to monitor rehabilitation and family training, access to valuable and strategic potential instrument, is constantly growing [2].

The representative upper arm rehabilitation robot is MIT-Manus developed by the United States MIT University, ARM Guide developed by the University of California and T-WREX[3],. In addition, there are HWARD, Gentle / G, RUPERT and other arm assisted rehabilitation system. Hocoma developed lower limb rehabilitation robot Lokomat, which is composed of supporting part, robot gait corrector and treadmill. Similar rehabilitation robot system also includes LokoHelp, ReoAmbulator, ARTHuR, ALEX, LOPES[4], etc. For the rehabilitation of patients with paralysis robot system is mainly through the auxiliary body movement to achieve muscle training, enhance tolerance, joint flexibility and movement coordination

Although this robots are effective in rehabilitation stage for the stroke patient, the number of robot is not enough to meet the needs of patience. And the stage of rehabilitation should be considered by doctor to change the mode or style of rehabilitation robots. As it should vary from person to person, the current rehabilitation programs can be costly.

The key factor in assessing a rehabilitation process is how much improvement is achieved during the treatment period. With the growing number of stroke populations, a large amount of research expenditure is devoted to finding automated solutions to improve the effectiveness and cost-effectiveness of post-stroke rehabilitation[5]. Many tools and methods can be used for this purpose, including kinematics, electromyography(sEMG), and brain activity analysis[6].

Clinical assessment is very important in stroke rehabilitation training for the increasing needs of measure the rehabilitation status and track the progress of rehabilitation. Traditionally, it was evaluated by clinicians on the basis of experience or traditional chart control method, which was inefficient and subjective. It had been proved that sEMG signals can be used to automatically evaluate the rehabilitation of stroke patients. In this paper, a classifier based on sEMG signals are proposed[7] . At the end of the paper, the validity and feasibility of this method are verified.

II. Methods of Rehabilitation Evaluation

Assessments are mostly performed manually by professional rehabilitation specialists using an icon-based sequential scale such as the recovery of Brunnstorm stage, Fugl-Meyer Assessment, or National Institutes of Health Stroke Scale [8]

The Brunnstrom Approach prescribes the stages of recovery of hemiplegia after stroke was developed by a physical therapist Signe Brunnstrom from Swedish. He emphasises the importance of the synergic pattern of movement which develops during recovery. This approach encourages development of flexor and extensor synergies during early recovery, with the intention that synergic activation of muscles will, with training, transition into voluntary activation of movements. This method suggests enlarging the synergistic effect of flexor and extensor muscles at the early stage of recovery. The purpose of this method is to transform the synergistic activation of muscles into automatic activation through training.

The Fugl Meyer Assessment (FMA) of Physical Performance is another scale which is widely used [9]. The FMA scale includes five scales that relate to various aspects of a patient's upper and lower limb in different scales. The scales are as Motor, Balance, Joint, Sensation, Range of Motion, Pain.

Generally, this kind of method are performed by professional experts using chart-based ordinal scales. It's inefficient and what's more, lacking efficiency in communication and lead to difficulty between different institutes and regions.

In this paper, a combination of characteristics of the rehabilitation phase classification methods are proposed to quantify rehabilitation phase which will allows doctors be more convenient for rehabilitation policy adjustment.

III. Feature Extraction for Semg Signals

There are many feature extraction methods for sEMG signals in time domain, frequency domain and time-frequency domain. Considering the characteristics of signals and combining with clinical practice and their characteristics in these aspects, this paper presents three aspects[10].

A. An Analysis Method in the Time Domain

The time domain features of s sEMG signals are easy to extract while the frequency domain features are stable. SsEMG signals are a complex signals which is usually not stable. It has energy distribution no matter in time space or frequency space. It's not easy to analysis sEMG signals either in time space or in frequency space. Over last few years, there are lots of techniques have been applied to analyze the energy features of sEMG signals in the time or frequency domain. The sample time domain or frequency domain, such as root mean square(RMS), mean power frequency(MPF), short-time transform(STFT) and so on.

Root mean square(RMS) describes the average change of signals amplitude, which means the mean value of signals. It has great significance in describing the physical characteristics of signals. Although it can reflect the change of sEMG amplitude with time in time dimension, it can not reflect changes in sEMG in detail. Its definition is as follows:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} x^2(i)} \qquad (1)$$

Where the x(i) is the sEMG value , and i = (0,1,2…N-1). N is the total length of the figure.

The iEMG value is the total discharge per motor unit of neuromuscular activity in a certain time range can reflect the fluctuation of sEMG signals with time. The definition of it is as follow:

$$\text{i}EMG = \frac{1}{N}\sum_{i=0}^{N-1}\left|x(i)\right| \qquad (2)$$

Where the x(i) is sEMG value , and i=(0,1,2…N-1), 。 N is the total length of the figure. N is data length.

In addition, the co-contraction Ratio (CR) of muscle refers to the proportion of antagonist muscles to the total of actin muscles in the process of bending and stretching. Studies have found that abnormal muscle tension is generally closely related to muscle synergy.

Where the subscript antagonist and agonist denotes antagonistic muscle and prime muscle.

B. An Analysis Method in the Frequency Domain

Although the frequency domain feature is much more difficult than the time domain feature extraction, it is found that the time domain features of s sEMG, such as iEMG and RMS, are not small and volatile when the muscle tension does not change significantly. However, after processing signals by frequency domain analysis methods such as Fourier transform, it is found that there is no obvious fluctuation in the frequency values of signals. The waveform of the frequency component is relatively stable in the spectrum. This shows that from the point of view of signals stability, the immunity of frequency-domain features is better than that of time-domain features, which has attracted much attention of researchers.

Mean Power Frequency (MPF) is a biological index[11]. Its magnitude is related to the consistency level of motor unit action potential and the speed of conduction. It can describe the frequency characteristics of sEMG signals.

The formulas are as follows:

$$MPF = \frac{\int_0^\infty f p(f)df}{\int_0^\infty p(f)df} \qquad (3)$$

Where p(f) represents power spectrum density function of sEMG Signals.

Recent years, researcher often combine the two different ways together to get a better result. This chapter proves the feasibility of using sEMG features to evaluate the rehabilitation stage through experiments, and compares the extracted features.

In this paper, IsEMG describes the total discharges of all participating muscles over a period of time. RMS, as the root mean square value, describes motor units numbers which activated during muscle activity, the types of motor units involved and the degree of synchronization. MPF describes the frequency value corresponding to the average power in the power spectrum of the fast Fourier transform results of all sEMG signals participating in the activity at a certain time point. It is a common index to judge muscle fatigue and is related to the speed of action potential transmission. MF is the median frequency, which is the result of fast Fourier transform of all sEMG signals at a certain time point - half of the area of the power spectrum in the power spectrum corresponds to the frequency value[12]. It reflects the middle value of the discharge frequency of the moving unit.

IV. Experiments and Results

A. Experimental Set up

Because of the influence of different nerve pathways and motor dysfunction, human left-hand and right-hand locus and coordination ability are different. In this chapter, the left-elbow is used to simulate the patient's impaired side and the right-elbow is used to simulate the patient's healthy side. As a result, it is found that IsEMG and RMS MPF have obvious differences on both sides. It is feasible to evaluate the rehabilitation stage through these characteristics.

As there are so many features in time domain such as root mean square and so on. And in frequency domain we can also calculate many features, it's important to find out which feature is better. These experiments are designed to collect features that are sensitive to muscle force changes for subsequent rehabilitation assessment.

The experiment is designed as follow:

We use disposable surface electrodes with a diameter of 5 cm to collect the sEMG data. The electrodes were attached to biceps brachii, triceps brachii, flexor carpi ulnaris and brachioradialis. The sampling frequency was 1000Hz. Fig.1 is a picture of sEMG signals acquisition equipment.

In this study, eight healthy person were selected, including six males and one female[13]. The physical condition of the volunteers is shown in the table. Before participating in the experiment, each volunteer knew the purpose of the experiment and the entire experimental process.

The experiment extracted sEMG signals from four muscles on left side of the subject, which were biceps, triceps, ulnar wrist flexors, and diaphragms. The positions of the muscles and the corresponding surface electrodes are as shown. In order to obtain high-quality sEMG signals, the subjects first cleaned the surface skin with a small amount of 75% medical alcohol to remove surface oils and other impurities before the start of the experiment. Each subject's hand is flush with the chest first, then repeat straighten the hands. Each time touch 2s, return to the original position for 2s, repeat 10 motion cycles[14]. Keep your body and head as static as possible during exercise. Fig. 2 is the waveform diagram during the measurement of sEMG signals.

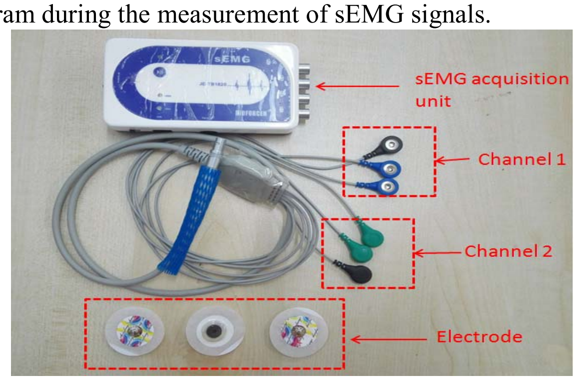
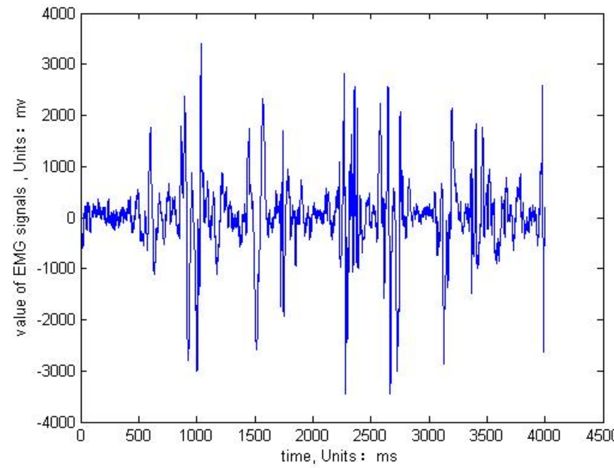
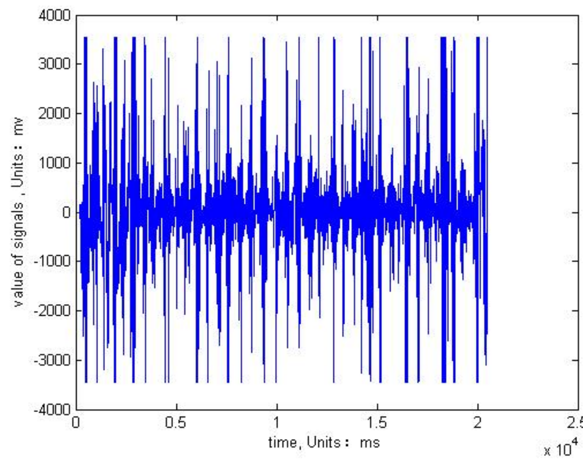


Fig.1 sEMG signals acquisition equipment and the equipment



(a) Local amplification figure



(b) Image of the complete signal

Fig.2 Raw sEMG signals

B. Experimental Results

After the experiment, we collect some sEMG data, from the data we can get some conclusions throuogh calculation.

The sEMG signals were set into serial group. And relevant data, such as RMS and iEMG values, were calculated in both time domain and frequency domain, respectively, as the evaluation criteria. Through analysis of the data, it is found that the values of the left and right hands have obvious discrimination[15]. sEMG signals can be used as the standard for rehabilitation evaluation. After various features are extracted and compared, the iEMG, RMS MPF MF are selected.

This experiment is set to compare different features from both domain in evaluating muscle strength. As the muscle strength has less different between left arm and right arm, the feature change a lot in the experiment might lead to better describe in muscle strength between different rehabilitation stage.

The following is a detailed analysis of the collected features.

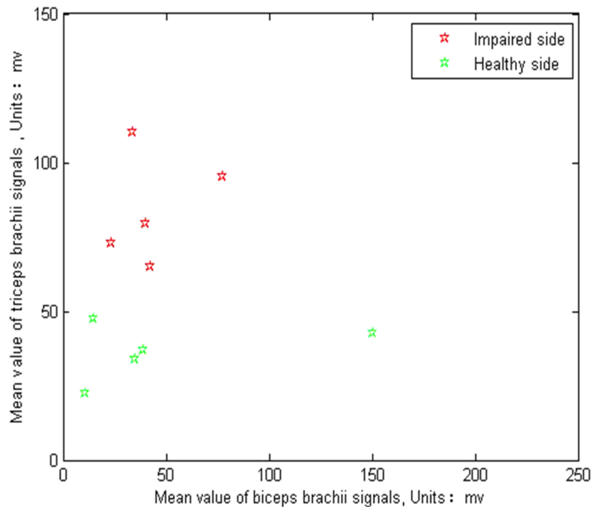


Fig.3. Mean value of the both signals

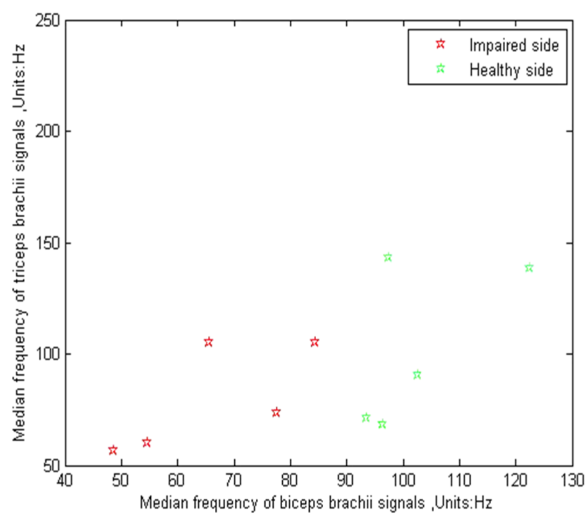


Fig.4. Median frequency of the both signals

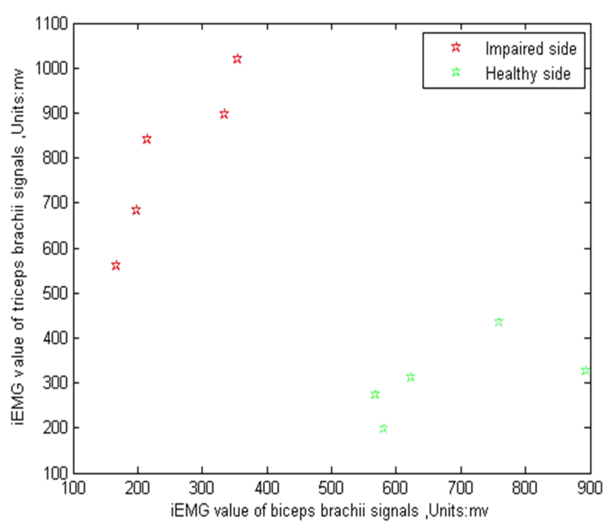


Fig.5. iEMG value of the both signals

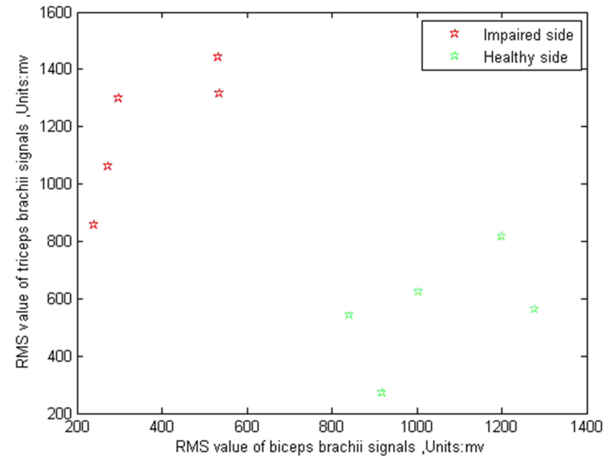


Fig.6. RMS value of the both signals

These above images in Fig.3, Fig.4, Fig.5 and Fig.6 are matlab image of the extracted time-domain and frequency-domain features. The transverse coordinate is the corresponding characteristic of biceps brachii muscle, and the longitudinal coordinate is the corresponding characteristic of triceps brachiiw muscle[16]. As can be seen in the figure, the RMS value, average value, integral sEMG value, median frequency and average power frequency of impaired side and healthy side have obvious distinction, which can reflect the difference of the exercise execution ability between impaired side and healthy side. RMS is used to reflect the time-domain assignment of the action, and median frequency and power frequency are used to reflect the stability of the spectrum action.

C. Analysis of Experimental Results

After several distinguishing features are obtained, the next step is how to quantify these features concretely and draw conclusions[17]. In this paper, we use the sEMG data to distinguish the impaired side from the healthy side.The Data relationships diagram is shown in Fig.7.

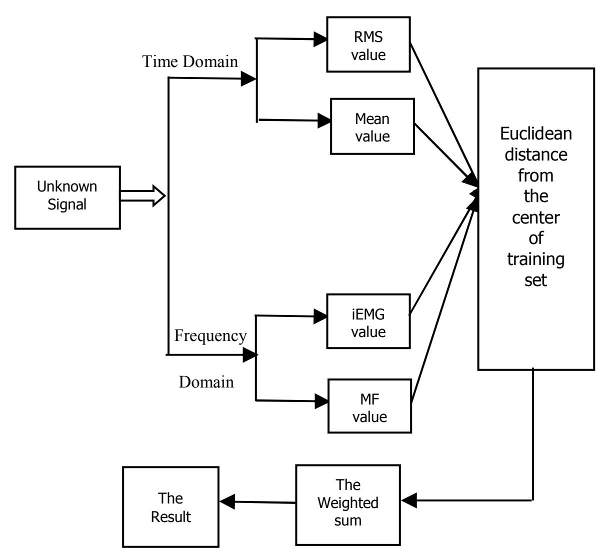


Fig.7. Data relationships diagram

The method used in this paper is based on the idea of naive Bayesian classifier, which is simplified without reducing the accuracy.

We can evaluate the rehabilitation stage by those features, as they are sensitive to the muscle strength. TABLE I [19] is a classical standard for muscle strength evaluate in rehabilitation fields.

TABLE I
MMT MUSCLE STRENGTH STAGE

STAGE	GRADE	CRITERIA	% TO STANDARD
5	N	Resistance to resistance and gravity	100
4	G	Can resist resistance, weaker than normal people	75
3	F+	Able to resist gravity	50
2	F	Unable to resist gravity	25
1	T	With slight contraction	10
0	Z	No contraction force at all	0

N:Normal G:Great F:fare T:trace Z:zero

Previous studies have shown that iEMG RMS and AVE are linearly correlated with muscle strength, while MPF and MF are linearly correlated with the slope of muscle strength decline. The algorithm counts iEMG, MF and RMS characteristics the signal, and gives different weights based on the reliability of different features.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \qquad (4)$$

Where the β(i) is the weight , and x is the different feature. The weight is calculated by the experiment. The weighted superposition of the results based on each feature is compared with the weighted superposition of the mathematical expectation of each feature, and the final judgment result is obtained[18]. The table are as follow:

TABLE II
VALUE OF EACH FEATURE

GROUP	AVE	IEMG	RMS	MF	MPF
1	40.08	355.38	531.7	54.49	290.13
2	57.41	333.91	534.25	65.48	251.54
3	33.53	214.24	298.93	77.48	317.24
4	42.09	197.74	273.80	84.48	314.44
5	23.32	167.70	238.98	58.49	269.37
average	43.29	253.79	375.53	66.08	268.54

AVE: average IEMG: Integrated Electromyogram RMS: root mean square
MF: median frequency MPF: mean power frequency

Initially collected sEMG data are divided into two groups, training set and verification set. In order to evaluate the algorithm, 30 groups of 4000 sEMG segments from different starting points were collected from the verification set in the evaluation stage of the algorithm. These signals are input into the classification algorithm to recognize the healthy side and the sick side. After recognition, the results obtained are compared with the correct results, and the comparison results are recorded. As a result, there are only two errors in the 30 sets of sEMG signals.

According to the hemiplegia rehabilitation theory[20] combined with sEMG signals, a new method aims to evaluate the rehabilitation stage is proposed in this chapters. Under the full understanding of the research progress in existing rehabilitation robots at home and abroad, there is no unified objective standard for the existing rehabilitation evaluation and the serious shortage of rehabilitation doctors. The method of classification of sEMG signals was carried out in the rehabilitation stage, and its feasibility was verified by simulation experiments. This method allows the patient to estimate his or her recovery stage without the need of a physician's assistance. Unified objective evaluation criteria also facilitate communication between doctors.

This algorithm is limited in simpler cases and sensitive to interference. But in certain fields it is better than similar algorithms. Compared with traditional method in the evaluate of rehabilitation stage, this method can let patients be free from the limitation of lacking professional doctors. They can even do all the steps at home. Doctors can also use this method to achieve an consistent results so that different hospitals or laboratory can communicate with each other conveniently. Compared with other algorithms for the same purpose, this method is simple but effective, it can achieve final result in less time while keep similar accurate rate.

V. CONCLUSIONS

In this paper, a method of evaluating and classifying the rehabilitation stage by using sEMG signals are proposed. This method mainly utilizes sEMG signals, and after denoising feature extraction, finally obtains several features on the extracted both domain, which is feasible. Subsequent research will be conducted on how to refine the classification criteria autonomous classification of the rehabilitation phase. The research of this subject has facilitated the rehabilitation training in the field of upper limb rehabilitation medicine, expanded the evaluation method, and also helped to broaden the research ideas in related fields. The innovation of this paper lies in the new method of evaluating rehabilitation stage using sEMG signals are proposed and the feasibility of this method is proved. In addition, several features to evaluate muscle strength were summarized.

ACKNOWLEDGMENT

This research is supported by National Natural Science Foundation of China (61703305); Key Research Program of the Natural Science Foundation of Tianjin (18JCZDJC38500) and Innovative Cooperation Project of Tianjin Scientific and Technological Support (18PTZWHZ00090).

REFERENCES

[1] Songyuan Zhang, Qiang Fu, Shuxiang Guo, Yili Fu, "Coordinative Motion-based Bilateral Rehabilitation Training System with Exoskeleton and Haptic Devices for Biomedical Application", *Micromachines*, vol. 15, no. 4, pp. 9021-9037, 2018

[2] Songyuan Zhang , Shuxiang Guo, Baofeng Gao, Hideyuki Hirata, Hidenori Ishihara, "Design of a Novel Telerehabilitation System with a Force-Sensing Mechanism", *Sensors*, vol.15, no. 5, 2015.

[3] 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, 2017.

[4] Shahrol Mohamaddan, Annisa Jamali, Ana Sakura Zainal Abidin, Mohd Syahmi Jamaludin, Noor Aliah Abd Majid, Muhamad Fadzli Ashari ,Helmy Hazmi, "Development of Upper Limb Rehabilitation Robot Device for Home Setting", proceedings of the *2015 IEEE International Symposium on Robotics and Intelligent Sensors*, pp. 376 – 380, 2015.

[5] R.A.R.C. Gopura, D.S.V. Bandara, Kazuo Kiguchi, G.K.I. Mann, "Developments in hardware systems of active upper-limb exoskeleton robots: A review", *Robotics and Autonomous Systems*, vol. 75, no. 7. pp. 203–220, 2016.

[6] Nina Robson, Gim Song Soh , "sGeometric design of eight-bar wearable devices based on limb physiological contact task", *Mechanism and Machine Theory* ,vol. 100, no. 8. pp. 358–367, 2016.

[7] Shuxiang Guo, Muye Pang, Baofeng Gao, Hideyuki Hirata, Hidenori Ishihara. "Comparison of sEMG based Feature Extraction and Motion Classification Methods for Upper-limb Movement" . *Sensors*, vol. 15, pp. 9022-9038, 2015.

[8] Muye Pang, Shuxiang Guo, Qiang Huang, Hidenori Ishihara, Hideyuki Hirata, "Electromyography-Based Quantitative Representation Method for Upper-Limb Elbow Joint Angle in Sagittal Plane", *Journal of Medical and Biological Engineering (JMBE)*, vol. 36, no. 1. pp. 111-121, 2016

[9] Shuxiang Guo, Muye Pang, Baofeng Gao, Hideyuki Hirata, Hidenori Ishihara, "Comparison of ssEMG based Feature Extraction and Motion Classification Methods for Upper-limb Movement", *Sensors*, vol. 36, no. 1, pp. 142-151, 2015.

[10] S. S. Groothuis, G. Rusticelli, A. Zucchelli, S. Stramigioli, and R. Carloni, "The variable stiffness actuator vsaut-ii: Mechanical design, modeling, and identification", *IEEE/ASME Transactions on Mechatronics*, vol. 19, no. 2, pp. 589-597, 2014.

[11] S. Zhang, S. Guo, B. Gao, Q. Huang, M. Pang, H. Hirata, et al., "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, 2016.

[12] M. Pang, S. Guo, Q. Huang, H. Ishihara, and H. Hirata, "Electromyography-Based Quantitative Representation Method for Upper-Limb Elbow Joint Angle in Sagittal Plane", *Journal of Medical and Biological Engineering*, vol. 35, no. 2, pp. 165-177, 2015.

[13] 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*, vol. 15, no. 4, pp. 9022-9038, 2015.

[14] R. Gopura, D. Bandara, J. Gunasekara, and T. Jayawardane, "Recent trends in EMG-Based control methods for assistive robots", *Electrodiagnosis in new frontiers of clinical research*, pp. 237-268, 2014.

[15] Songyuan Zhang, Shuxiang Guo, Mohan Qu, Muye Pang. "Development of a Bilateral Rehabilitation Training System Using the Haptic Device and Inertia Sensors". Proceedings of *2014 IEEE International Conference on Mechatronics and Automation*, pp. 1237-1242, August 3-6, Tianjin, China, 2014.

[16] 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.

[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] 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.

[19] 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.

[20] 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.