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An EMG-based Muscle Force Evaluation Method Using Approximate Entropy

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Abstract - This paper proposed a novel muscle force evaluation method to evaluate the patient's rehabilitation condition in the process of rehabilitation training. According to the related literature research, the complexity of the electromyography (EMG) signals were different under different muscle force. The physiological features and the state of muscle can be indirectly speculated by detecting the change of the dynamic complexity of EMG signals. The novel ideal of our research is to propose an EMG-based muscle force evaluation method using approximate entropy. The evaluation system consists of two main parts: the EMG acquisition (BIOFORCEN) and the measurement of muscle force (FingerTPS). Experiments were conducted with a healthy male. 15 groups EMG signals of biceps and triceps were acquired under different muscle force. Raw EMG data were recorded for off-line analysis. The approximate entropy (ApEn) and the power of EMG signals aiming at intercept relatively stable 10 section signal in each group were calculated to compose the training set. In addition, the additional 150 groups feature vectors were obtained to compose a sample set. 15 groups muscle force were divided into 6 levels and two classification method (linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA)) were used to classify the feature vector. Experimental results have shown that the discrimination between ApEn and the power were obvious and 65% classification accuracy was got with the QDA method. The research of this paper can be a promising approach for further research in the field of rehabilitation evaluation.

***Index Terms* -Rehabilitation evaluation; Electromyography signals ; Approximate entropy (ApEn); Quadratic discriminate analysis (QDA)**

I. INTRODUCTION

Stroke is a leading cause of death in the world and its incidence is high in most countries, such as America, Netherlands and so on based on World Health Organization (WTO) and other reports [1]. Stroke is a disease, which is a sudden ischemic or hemorrhagic disturbance in the blood supply to brain tissue that results in partial loss of brain function and always leads to hemiplegic paralysis [2-3]. Patients with stroke always lose their ability of daily life (ADL), thus need care and treatment, which places a burden on society and families, especially in an aging population.

The traditional rehabilitation mainly depends on the experience of recovery physiotherapists. The involvement of human beings is a challenging job because it is a time-consuming and labour-intensive process[4].The new rehabilitation mainly adopts rehabilitation robots in training task[5]. Skin surface electromyography (sEMG), which is one of the biological signals, is often used to control the rehabilitation robot according to the user's intention since it directly reflects the user's muscle activity level in real time [6-8]. Moreover, the real-time evaluation for patient's recovery condition and active interaction control strategy that can provide appropriate and comfortable training or assistance is essentially necessary during rehabilitation [9]. Meanwhile, rehabilitation process need some objective and effective data to evaluate the effectiveness of rehabilitation training for setting better training program to enhance the level of recovery.

Conventionally, clinical evaluations are manually performed by experienced clinicians using chart-based ordinal scales. In early stage, Brunnstrom had presented Brunnstrom Gradational evaluation that he had divided the rehabilitation process into six stages and evaluated the rehabilitation condition according to the difference in each stage[10]. The Fugl-Meyer scale was developed as the first quantitative evaluative instrument for measuring sensor motor stroke recovery, which was based on Twitchell and Brunnstrom's concept of sequential stages of motor return in the hemiplegic stroke patient. The Fugl-Meyer is a well-designed, feasible and efficient clinical examination method that has been tested widely in the stroke population [11].

In recent years, Wen Ji etc have proposed an evaluation model of stroke rehabilitation and evaluated the condition of stroke patients quantitatively [12]. Experimental results have showed that the evaluation model of stroke rehabilitation correlated well with the Fugl-Meyer assessment, which indicated that the model was effective. Lan Wang etc have presented the rehabilitation training and evaluation system based on the force feedback device and real-time wireless sensor motion capture and mechanical evaluation system (FAB) [13].

Last year, Zhe Zhang etc in Australia have presented a objective assessment of upper limb mobility for post-stroke rehabilitation [14]. The proposed assessment system utilized the kinematic information automatically collecte during a regular rehabilitation training exercise using a wearable Inertial Measurement Unit. By calculating a single index, the system can efficiently generate objective and consistent quantitative results that can reflect the stroke patient's upper limb mobility.

At present, the rehabilitation evaluation is mainly in accordance with all sorts of scales to evaluate and score for limb damage by rehabilitation physician [15-16]. The shortcomings of these methods are that strong subjective experiential or single evaluation index etc. Moreover, rehabilitation physicians cannot not only carry out the sustained and standardized rehabilitation training, but fulfil a complete data record of the rehabilitation process. There is no a quantitative synthesis evaluation method making a reasonable rehabilitation training mode.

Our study focuses on the rehabilitation evaluation method based on the muscle force. EMG signals are analysed and processed to evaluate the degree of the recovery of muscle force for patients in the process of rehabilitation training. Because EMG signals are chaotic and its characteristic of nonlinear is obvious, the characteristic vector that the approximate entropy and the power of EMG signals are extracted to compose the training set. Through the quadratic discriminate analysis (QDA) method, the accuracy of classification is evaluated.

The rest parts of this paper are organized as follows: section II is devoted to the structure of evaluation system; section III propose the rehabilitation evaluation experimental including the approximate entropy theory and the experimental data analysis; in section IV, experimental results are demonstrated to verify the feasibility of our approach; finally, conclusions and future work are drawn.

II. The Structure of Evaluation System

In this paper, an EMG-based upper limb rehabilitation robot evaluation system was presented. The structure of evaluation system includes ULERD, surface electromyography (sEMG) acquisition system and PPS finger touch measurement system(FingerTPS).

A. The Upper Limb Exoskeleton Rehabilitation Device (ULERD)

In our study, the ULERD, as our rehabilitation training device, the design motivation of which is to provide effective training to the patients with motor dysfunction to recover the motor function of upper limb including elbow and wrist joints. The ULERD is ergonomically comfortable. Meanwhile, it is the aim to design such a wearable and portable device. Design process of ULERD can be obtained in detail from reference [17-18]. The structure of the ULERD from upper view is showed in Fig. 1. ULERD has three active DoFs including the elbow flexion/extension, forearm pronation/supination and wrist flexion/extension in elbow and wrist joint. Due to comfortable and suitable for home-rehabilitation to patients, it is necessary to decrease the mass of such device as light as possible. BLDC motor (Maxon Technology) which is used for the ULERD for its high power density to decrease the mass of the device. Meanwhile, main frames of this device are made of aluminum board. The total weight is 1.3kg.

B. EMG Acquisition System

In this paper, BIOFORCEN, a surface electromyography

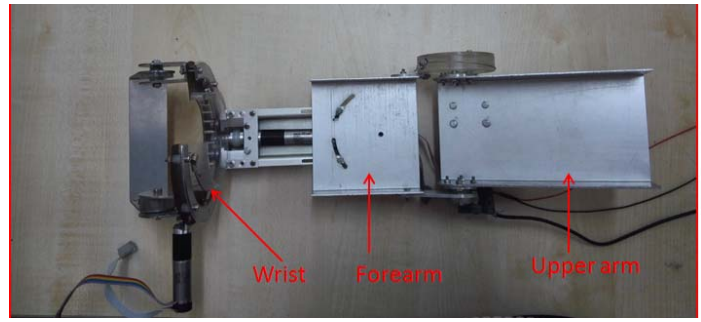

Fig. 1 The prototype of the upper limb exoskeleton rehabilitation device

acquisition system designed by Mr Intelligent technology co., LTD, are used to obtain the initial EMG signal. In addition, the BIOFORCEN system are equipped with two sEMG acquisition unit and each acquisition unit can collect 8 sEMG signals. As a result, a total of 16 channels sEMG signals can be collected at the same time. All EMG channels are equipped with a first order high-pass filter and cut-off frequency of 10 Hz; All EMG channels configures second-order Butter Worth low-pass filter and cut-off frequency of 3000 Hz; 8190k Bytes space and 20 record can be stored. The connection mode of acquisition unit and upper computer has two kinds: wired and wireless mode. Wired mode is achieved through the USB cable to realize online data transmission and the work environment are restricted due to the cable length limited. Contrast, wireless model is equipped with wireless interface unit to realize the data wireless transmission, which reduces the requirement for experimental environment. The BIOFORCEN system adopts differential acquisition methods and each channel have three electrodes (two records electrode, a reference electrode). The electrode, one-time patch type, is pasted on the surface of corresponding muscle to transmit sEMG data by connected to the electrode wire. The sEMG acquisition unit and the electrode are showed in Fig. 2.

C. FingerTPS

In order to verify the change of electromyography signal complexity under different muscle force, we collect the sEMG signal under different muscle force. However, muscle force is

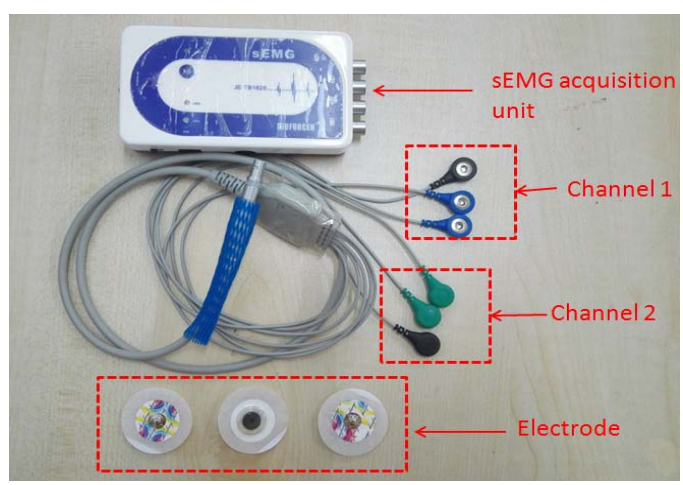

Fig. 2 The sEMG acquisition unit and the electrode

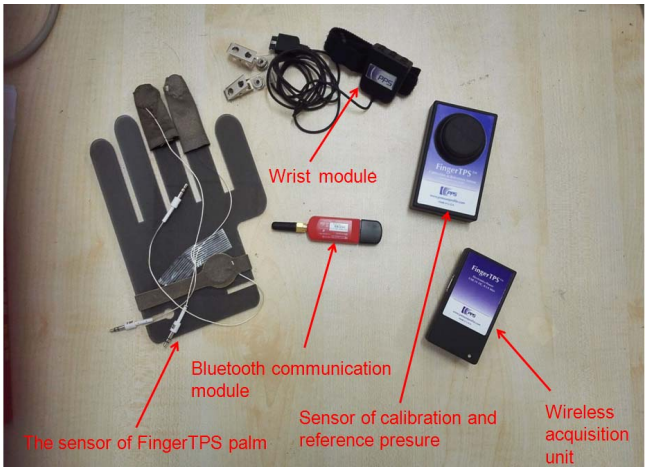

Fig. 3 FingerTPS touch measurement system

the force that produced by muscle active movement and because it is a physiological concept, it can't be measured precisely by existing equipment for measuring force. In this study, we set up a barrier in the palm of our hand in the process of elbow flexion to measure the size of the force between palm and the obstacles representing the size of muscle force.

In this paper, the PPS finger touch measurement system (FingerTPS) is used to measure the force between palm and the obstacles. The FingerTPS tactile measurement system uses the high sensitivity and the capacitive sensor reliably to measure the size of force. Accurate mechanics data and video images can be captured and displayed through PPS powerful Chameleon TVR software that can multi-function select the time series of the record, the real time, average and peak stress condition. The FingerTPS system is showed in Fig.3.

III. Evaluation Experiment of Muscle Force

According to the related literature research, the complexity of the EMG signal varied from different muscle force [19]. This paper presents a muscle force evaluation method based on the approximate entropy of EMG signal for making an objective evaluation for the degree of the recovery of muscle force for patients in the process of rehabilitation training.

Skin surface electromyography (sEMG) is the biological electrical signals that is acquired and recorded in the muscle or muscle groups, which is a external performance of group of nerve cells in the electrical activity. Some scholars pointed out that the number, discharge times and the transmission rate of nerve cell in muscle activity will appear obvious difference in the different movement modes and fatigue state, which is the change of complexity on the dynamics performance. The physiological features and the state of muscle or muscle groups can be indirectly speculated by detecting the change of the dynamic complexity of EMG signals.

A. *Approximate Entropy Theory*

Approximate entropy is defined as a conditional probability of similarity vector in by m to (m + 1) dimensions to maintain its similarity. Approximate entropy algorithm is as follows [20]:

1) Giving length N of one-dimensional time series$\{u(i), i = 1 \dots N\}$ and reconstruct m dimensional vector X_i $(i = 1,2, \dots n, n = N - m + 1)$according to (1):

$$X_i = \{u(i), u(i+1), \dots, u(i+m-1)\} \tag{1}$$

2) Calculate the distance d_{ij} between arbitrary vectorX_i and vector$X_j$$(j = 1,2, \dots N - m + 1, j \neq i)$ according to (2):

$$d_{ij} = \max|u(i+k) - u(j+k)|, k = 0,1, \dots m-1 \tag{2}$$

3) Giving the threshold r(r is between 0.2 and 0.3) and calculate $d_{ij} \leq r \times SD$ for each vectorX_i (SD is the for the standard deviation of sequence), and find the ratio of the number and the total number ,denoted by $C_i^m(i)$.

*4) T*aking the logarithm of $C_i^{m(i)}$and calculate the average value of all i, denoted by $\emptyset^m(r)$:

$$(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} lnC_i^m(r) \tag{3}$$

5) m increase 1 and repeat the step(1)-(4), counting $C_i^{m+1}(r)$and $\emptyset^{m+1}(r)$.

*6)*According to $\emptyset^m$ and $\emptyset^{m+1}$ and calculate approximate entropy(ApEn):

$$ApEn = \sum_{N\to\infty} |\emptyset^m - \emptyset^{m+1}| \tag{4}$$

B. Experimental Setup

EMG-based upper limb rehabilitation evaluation experiment include the sEMG signal acquisition, storage and analysis. The sEMG signal are obtained and stored to the database by the BIOFORCEN system. The database are divided into two kinds: contrast database and experiment database. The contrast database are used to store the sEMG signal of the patient normal side body to produce the contrast data; the experiment database are for storing the sEMG signal of needing evaluation and compare with the contrast data after processing to output the evaluation results.

Primary experiments were performed with a healthy male on his left hand. EMG signals of biceps and triceps under different muscle force are mainly collected in the experiment. Before placing the electrodes, the skin corresponding to biceps and triceps was shaved and cleaned with alcohol in order to reduce the skin impedance.

During experiments the fixed bracket as obstacles impeded subjects elbow flexion movement for measuring contact force between palms and stents corresponding to the size of muscle force during elbow flexion movement. Fig.4 shows the experiment platform of muscle force and EMG acquisition. Experiment collected the EMG signal data in 15 groups muscle force (0N、2N、4N、6N、8N、12N、14N、16N、18N、20N、22N、24N、26N、28N) and then power

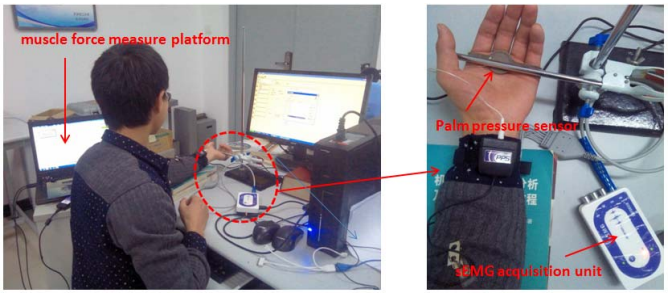

Fig.4 The experiment platform of muscle force and EMG acquisition

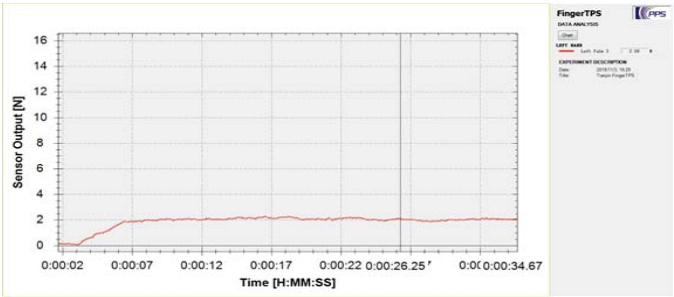

Fig.5 The muscle force curve of 2N

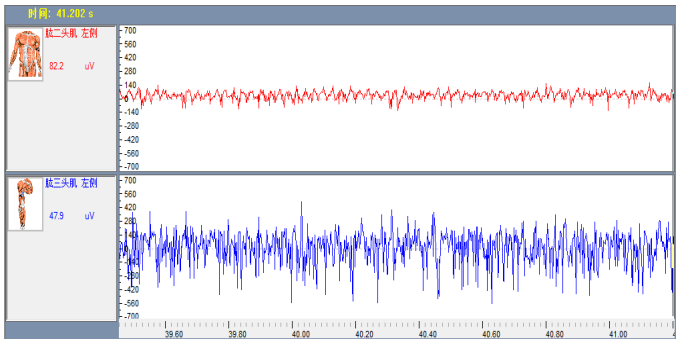

Fig.6 The EMG signal waveform of 2N muscle force

and ApEn of EMG signal in each group were calculated. The subject maintain the size of muscle force at a certain level (volatility less than 0.5 N) by observing the muscle force curve when collecting the EMG signal in each group. The muscle force curve of 2N is shown in fig.5 and the corresponding EMG signal waveform is shown in fig.6.

C. Data Analysis

The EMG signal are sampled at 1 kHz, experiment have collected 15 groups sEMG signal of the biceps and triceps and each group we intercept relatively stable 10 section signal for processing analysis, each section has 1000 sampling points. Firstly, elliptic filter is designed to filter 10-400Hz bandwidth for the collected EMG signal. Elliptic filter is relatively narrow transition zone than other digital filters in the same order and has a smaller pass-band and stop-band ripple. Then EMG energy $\mathrm{Power_k}$ and approximate entropy $\mathrm{ApEn_k}$ of each section are counted, respectively ,where, k = 1, 2 ... 10. At the same time, the average energy of power and approximate entropy of 10 section EMG signal under each muscle force and variance STD are calculated. Fig.7 shows the relation between the average power of EMG and the average energy EMG approximate entropy. Fig.8 shows the relation between the average power of EMG and the muscle force F.

It can also be seen from the fig.6 that the power of biceps is more concentrative in flexing motion and the ApEn is concentrated between 1.55 and 1.65; on the contrary, the power and the ApEn of triceps has been rather dispersed and it increased with the increase of the power of EMG.

In order to acquire the more accurate corresponding relation of muscle force, approximate entropy and the power of EMG , we take the standardized processing of the power of EMG and approximate entropy as following:

$$Power = Power_T - Power_B \tag{5}$$

$$ApEn = \frac{ApEn_B}{ApEn_B + ApEn_T} \tag{6}$$

Where, Power is the EMG power after standardized processing, $\mathrm{Power_T}$ is the EMG power of triceps, $\mathrm{Power_B}$ is the EMG power of biceps. ApEn is the approximate entropy after standardized processing, $\mathrm{ApEn_T}$ is the approximate entropy of triceps, $\mathrm{ApEn_B}$ is the approximate entropy of biceps.

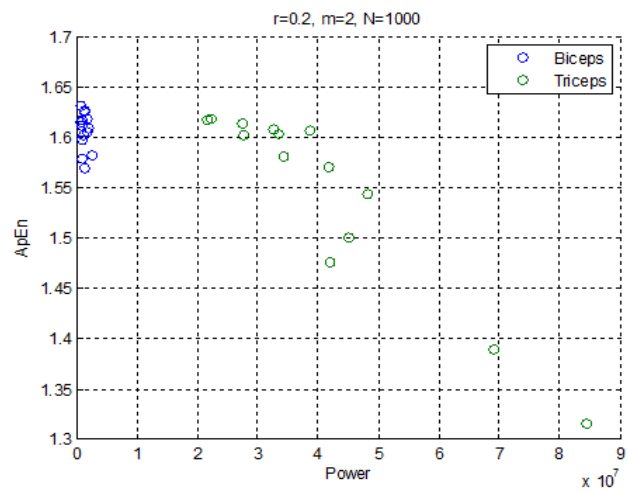

Fig. 7 Relation diagram of the average energy of power and ApEn

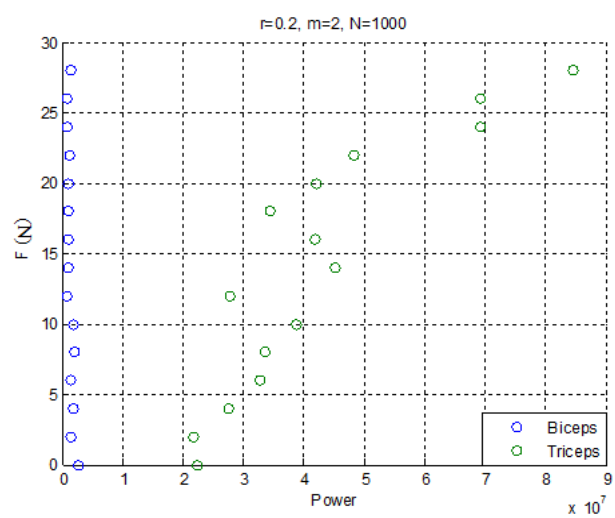

Fig. 8 Relation diagram of the average energy of power and the muscle force

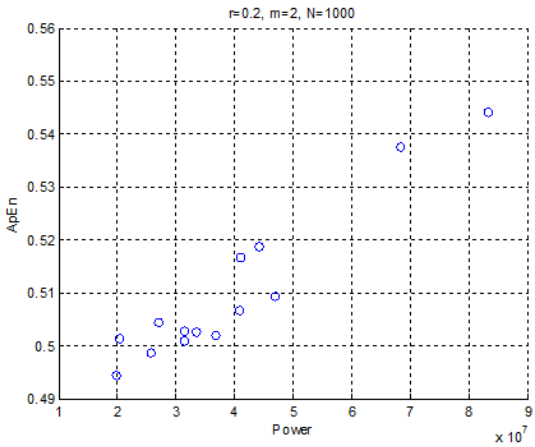

Fig. 9 Relation diagram of the approximate entropy and the power of EMG power after standardized processing .

Fig.9 shows the relation between the approximate entropy and the power of EMG power after standardized processing . We can see that the discrimination between ApEn and the power is better.

IV Experimental Results

We divide the size of muscle force into six grades(Level 1 ~ Level 6) and each level corresponding the size of muscle force is shown in table 1.

150 groups data of approximate entropy of EMG signal and power of EMG signal from the experiment are standardized. The approximate entropy and power after processing are composed the two-dimensional feature vector for constructing training set. The distribution of the training set data is shown in Fig.10, where, different colours and shapes distinguish different levels of muscle force. In addition, the additional 150 groups feature vectors are obtained to compose a sample set .

In this paper, we have adopted two classification method(linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA)) to classify the feature vector. The two classifier are trained with training set in Matlab firstly, and then use the trained classifier to classify sample set. The classification result of two classification method and the accuracy of classification are obtained, as shown in Table 2 and Table 3.

Table 1 Muscle force hierarchy

The grade of muscle force	Leve l 1	Level 2	Level 3	Level 4	Level 5	Level 6
The size of muscle force（N）	0~5	5~10	10~15	15~20	20~25	25~30

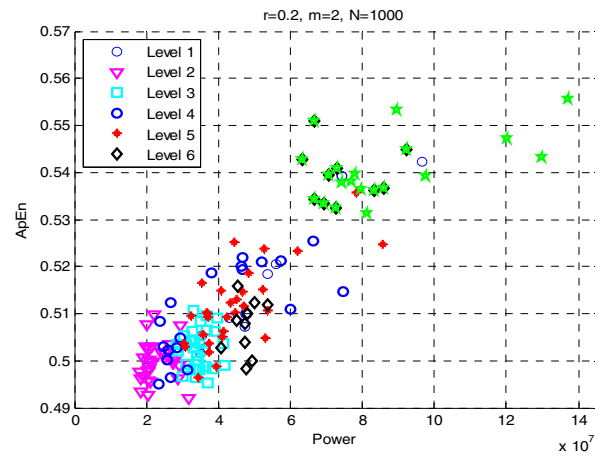

Fig. 10 Grade distribution of approximate entropy and muscle force

Table 2 The classification result of LDA

The grade of muscle force	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
The number of sample	30	30	20	30	20	20
The number of correct	24	20	5	11	2	20
The number of error	6	10	15	19	18	0
accuracy	80%	66.7%	25%	36.7%	10%	100%
The overall accuracy	55%					

Table 3 The classification result of QDA

The grade of muscle force	Level 1	Level 2	Level 3	Level 4	Level 5	Leve l6
The number of sample	30	30	20	30	20	20
The number of correct	24	23	5	10	11	16
The number of error	6	7	15	20	9	4
accuracy	80%	76.7%	25%	33.3%	55%	80%
The overall accuracy	65%					

Obviously, the classification error of QDA is smaller, in addition to Level 3 and Level 4, the accuracy of classification of other levels reached more than 55%, the overall accuracy reached 65%.The reason that the Level 3 and Level 4 classification is not very ideal may be the cause of the following aspects: the resolution of alternative characteristic values in the muscle force segment is poor because of the restricted by eigenvector dimension; Muscle fatigue in the some muscle force section affects the characteristic value of EMG signal , which affects the accuracy of classification .

The effect diagram of QDA classification is showed in Fig.11. In figure, different colours background regions correspond to different muscle force grading. If the feature values fall respective regional, the classification is correct, otherwise explained misclassification. It can also be seen from the Fig.11, the results of classification of Level1、Leve2 and Level 6 are better .

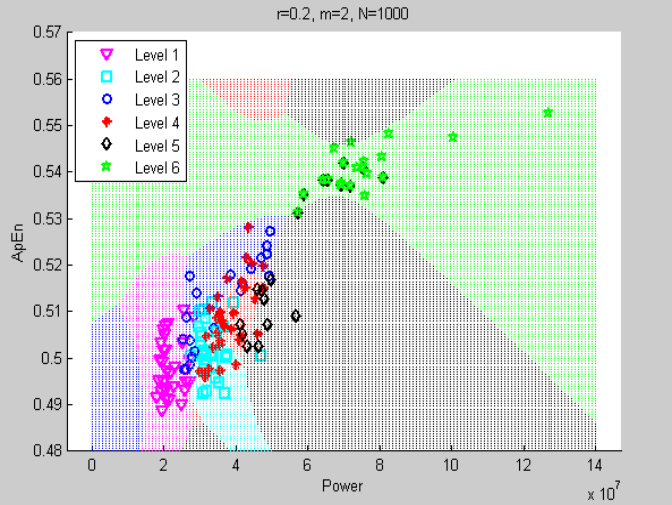

Fig. 11 The effect diagram of QDA classification

IV. Conclusions and Future Work

In this paper, a muscle force evaluation method based on the approximate entropy of EMG signal is proposed. We collected the EMG signal under different muscle force forming a contrast database to evaluate the degree of the recovery of muscle force for patients in the process of rehabilitation training. The EMG signal of a healthy male were extracted by BIOFORCEN system. The approximate entropy and the power of EMG signal were extracted to constitute a two-dimensional characteristic vector in rehabilitation evaluation experiment. 150 groups training set and sample set were obtained, respectively. 15 groups muscle force were divided into 6 levels and two classification method (linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA)) were used to classify the feature vector. The accuracy of classification of QDA reached 65%. Experimental results showed that the rehabilitation evaluation method is accurate and efficient.

The accuracy of classification for further research is to be improved. On the other hand, the muscle fatigue in the process of training should be taken into consideration.

Acknowledgment

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