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Extraction of sEMG Signal in Upper Limb Rehabilitation Robot

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Abstract: The limb motor dysfunction caused by cerebral injury brings a heavy burden to the patients family and society. The scientific rehabilitation training helps a lot in the recovery of limb motor function. The treatment of nerve rehabilitation is a hard work. At present, it mainly relies on the hand operation of rehabilitation physician to take rehabilitation exercises. It limits the improvement of rehabilitation. The combination of rehabilitation medicine and robot technology improves the efficiency of rehabilitation training and ensures the strength of action training, which has created a new way for the research on new rehabilitation technology. With the interdisciplinary development and integration, the rehabilitation medicine and the rehabilitation robot has been further studied and explored. The sEMG signal is one of the most important data in the limb rehabilitation, especially in upper limb rehabilitation robot. In the development of rehabilitation robot, the extraction of sEMG signal in upper limb rehabilitation is investigated deeply. The paper focuses on the status of the extraction of sEMG signal. In the end, the development trend for the future is discussed.

Keywords: sEMG signal, upper limb rehabilitation, extraction.

1 Introduction

With the improvement of social life and the progress of modern medicine, more and more people have opportunities to enjoy the life without worry about hunger or sick. The better life promotes the longevity rising, which results in the growing number of elderly people. China is stepping into the aging society with many other countries in the world. At the same time, with the accelerated pace of modern life, the number of hemiplegia people increases because of the cardiovascular diseases and nervous system diseases. The age of onset tends to be younger[1].Also, the number of physical disabled people is increasing, especially those who have upper limb disorders. Loss of upper limb movement or hemiplegia greatly affects patients daily life. In the past years, the rehabilitation largely depends on the physical treatment [2,3,4,5,6]. This method is time-consuming and laborious.

Nowadays, the development of robot technology provides a good opportunity for the research on rehabilitation training robots. This type of robot is used to help limb dysfunction patients in completing limbs motion. So that part of the patient's movement can be restored. The using of robotic technology improves the scientific of the rehabilitation training. Meanwhile, doctors are free from heavy manual labors and focus on developing better rehabilitation programs to improve the rehabilitation efficiency[7]. Some famous rehabilitation robots are shown in the fig.1 to fig.3.

An important part of rehabilitation training robots is the sEMG (surface electromyogram) signal. The electrical activity of the human neuromuscular system reflects the muscle movement, and it can be obtained by measuring the sEMG signal at the surface of the skin. Because it is convenient to be acquired and has no trauma to the human body, the multi-channel sEMG signal is used to achieve the myoelectric control of upper limb

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rehabilitation training robot. It has become a research hotspot in the field of rehabilitation engineering. The myoelectric control theory based on pattern recognition is to extract signal characteristics of different upper limb movements from the multi-channel sEMG signals [8]. Then, the pattern classifier recognizes the target action mode to realize the motor control of upper limb rehabilitation robot. For the study of sEMG control based on pattern recognition, the evaluation index mainly includes recognition accuracy and computational speed. The research object of this paper is to take a review which mainly focuses on the extraction of sEMG signal in upper limb rehabilitation robot.

Figure. 1 Planar module of MIT-MANUS

Figure. 2 Assisted Rehabilitation and Measurement Guide

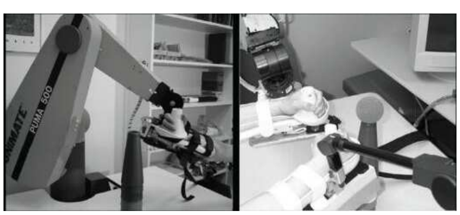

Figure. 3 Mirror-imaginable robot-assisted therapy workstation

2 OVERVIEW OF THE SEMG SIGNAL EXTRACTION

A wide range of research on the rehabilitation training robot has been carried out. In 1791, Galvani confirmed that muscle contraction was closely related to electricity. After that, the research on nerve impulse conduction emerges in endlessly. In 1849, biologist Du Bois-Reymond discovered that the electrical activity with an activation of muscle contraction can be recorded. Forty-one years later, Marey first recorded this electrical activity which is electromyogram (EMG)[9]. Then, people found that human bio electricity changes along with the physiological function. According to this feature, electroencephalogram (EEG), electrogastrogram (EGG), surface electromyogram (sEMG) and other instruments were invented. Among these instruments,sEMG signal reflects the activity of nerve muscle in a certain extent, which has characteristics of noninvasive, real-time and multi-target measurement. As a result, sEMG technique is widely used in the field of rehabilitation medicine, sports science and so on.

At present, the research of sEMG signal can be divided in two parts. One is to analyze and research the physiological information of sEMG signal. This research focuses on finding the relationship between muscle internal physiological or biochemical processes and the EMG signal changes. It is mostly applied in diagnosis and motor function evaluation of neuromuscular diseases, ergonomic analysis of muscle work, fatigue assessment in sports science and so on [10]. Another part is to identify sEMG signal corresponding to each limb movement. The research findings are widely used in human-computer interaction, clinical rehabilitation and so on. Also, sEMG signal needs to be analyzed in each part. Traditional methods include time domain analysis, frequency domain analysis and time frequency analysis [11]. Some characteristics are the classic indexes to evaluate the fatigue characteristics of muscle movement, such as average amplitude (AEMG), root mean square (RMS) in time domain and mean power frequency (MPF), mean frequency (MF) in frequency domain [12]. In recent years, the continuous development of analysis technology makes it possible to explore new methods in nonlinear analysis of sEMG signal, such as fractal, Lyapunov exponent, entropy, complexity and so on. These methods provides new thinking in finding the relationship between sEMG signal and upper limb motion [13,14,15].

The general process in autonomous training program based on movement extraction of sEMG signal is divided into five stages. The first stage is to judge the movement. Surface electrodes are located on the upper limb to detect the sEMG signal of movement before the judgment. The judgment accords to the detected data, and this judgment system is already set. After the effective movement is recognized, the sEMG signal can be collected at the same time. The second stage is to analyze the sEMG signal and extract the characteristics. This step is mainly about extracting the feature vectors by effective analysis method to realize the data dimension reduction. The third stage is to create the supervised learning system by pattern classifier. Pattern classifier should be set at the beginning. Then, to program the movement reasonably. Next step is to set the sEMG feature vectors according to the specific movement as the input data. The movement program is set to be output data. Last step is to train the supervised learning system until the classifier is convergence. The fourth stage is to recognize the pattern. The sEMG feature vectors are inputted into trained pattern classifier to recognize the current movement. The fifth stage is to perform the movement [16,17,18,19,20].

3 THE EXTRACTION OF SEMG SIGNAL

The sEMG signal extraction is a very important part in the recognition. The selection of characteristic vector is directly related to the extraction ability of the recognition system [21,22,23,24,25]. For the multi-channel sEMG control of rehabilitation robot, it is a fundamental problem to find valid sEMG features to characterize muscle movement. In recent years, the research on the sEMG signal extraction is developing rapidly. On the basis of research, variety of methods for the sEMG signal extraction can be chosen. Then, feature vectors which are extracted should be analyzed and compared to select the optimal feature extraction method and the best feature vector. The methods of feature extraction of sEMG signal are divided into three categories: frequency-domain analysis, time-domain analysis and time-frequency analysis [26,27].

3.1 FREQUENCE-DOMAIN ANALYSIS

In the frequency-domain analysis, the main analysis method is to carry on the fast Fourier transform (FFT) on the sEMG signal to obtain the frequency spectrum or power spectrum which reflects the change of the sEMG signal in different frequency components. So it could reflect the change of the sEMG signal in the frequency dimension[28]. For the quantitative characterized of the sEMG spectrum or power spectrum, the researchers use the following two indicators to research, that is, mean power frequency (MPF) and median frequency (MF). The calculation can be shown as Equation (1)and Equation (2). The frequency-domain description of EMG signal is relatively stable, which directly leads to the stability of frequency-domain characteristics extracted by the power spectrum. So, the extracted frequency-domain characteristics are favorable to the pattern extraction of EMG signals [29,30,31].

$$MPF = \frac{\int_0^\infty fP(f)\,df}{\int_0^\infty P(f)\,df} \tag{1}$$

$$\int_0^{MF} P(f)df = \int_{MF}^\infty P(f)df = \frac{1}{2}\int_0^\infty P(f)\,df \tag{2}$$

3.2 TIME-DOMAIN ANALYSIS

In time-domain methods, the sEMG signal is recognized as the time function which extracts its statistical characteristics for the sEMG extraction. The characteristics include the average value (AV), the integral EMG (iEMG), the root mean square (RMS), absolute value integration (IAV), zero crossing point (ZC), variance (VAR), Willson amplitude (WAMP) and so on. Time-domain analysis parameters are often used in reflecting real-time and no injuries muscle activity states, which has good real-time performance. Each value has its own characteristics [32,33,34,35].

The separability of average value (AV) is not strong. Because the EMG signal approximates a mean zero random signal and the mean differences of each channel is not obvious in all kinds of movements.

The classes distance between absolute value integration (IAV) is very large. It has the considerable separability and small standard deviation, which indicates that the distance is larger within classes and clustering is better. The absolute value integration is the sum of the area under the sEMG signal curve in the unit time, which reflects the changes of the sEMG signal over time.

The zero crossing point (ZC) is the number of positive and negative crossings of zero, which takes the distribution of different data points into account. The zero crossing point reflects the frequency of the sEMG signal which has small differences in characteristics. This shows that the short time data sample has a very small distance between the numbers of zero crossing point and clustering is poor.

The IEMG and RMS are the most common, which reflects the variation of muscle electrical signal amplitude in the time dimension. The root mean square (RMS) directly relates to the electric power of the sEMG signal, which depends on the intrinsic connection between muscle load factor and physiological and biochemical process. So, the root mean square (RMS) has more direct physical meaning. The calculation of IEMG and RMS are as Equation (3)and Equation (4).

$$iEMG = \int_t^{t+T} |EMG(t)|dt \tag{3}$$

$$RMS = \sqrt{\frac{\int_t^{t+T} EMG^2(t)\,dt}{T}} \tag{4}$$

3.3 TIME-FREQUENCE ANALYSIS

The traditional Fourier transform only describes the global frequency characteristics of the signal, and the frequency information of the signal is not available in any time-domain. The time-frequency domain analysis method can be used to analyze the time domain and frequency domain. The time-frequency analysis method of the EMG signal is mainly concerned with the short-term Fourier transform, Wigner-Ville transform and wavelet transform [36,37,38].

3.3.1 SHORT-TERM FOURIER TRANSFORM

The short-term Fourier transform is put forward in 1946 by Gabor. The basic idea of the transformation is that the non-stationary signal is regarded as the composition of a series of short time stationary signals in the framework of the Fourier transform. The character of short time can be obtained by adding the window in time domain [39,40].

The short-term Fourier transform is defined as follows. When the signal is $f(t) \in L^2(R)$, the short-term Fourier transform is $Gf(\varpi,\tau) = \int_{-\infty}^{+\infty} f(t)g(t-\tau)e^{-j\varpi t}dt.g(t)$ is the window function.

Cai Liyu et al. analyze the sEMG signal using the short-term Fourier transform, and extract feature vectors by singular value decomposition to carry out the pattern recognition of four hand motions[41].

3.3.2 WIGNER-VILLE TRANSFORM

Wigner-Ville distribution is the distribution of signal energy in time and frequency. It has many advantages. For example, it has the identity and the inversion property in the definition domain, which makes it has the potential to deal with the non-stationary signal [42].

The definition of Wigner-Ville transform is as follows.$WV(t,\omega) = \int_{-\infty}^{\infty} s\left(t+\frac{\tau}{2}\right) \cdot s^*\left(t-\frac{\tau}{2}\right) e^{-j\omega t} d\tau$. $s(t)$and$s^*(t)$are the conjugate complex number. t refers to time. f refers to frequency. τ refers to time delay.The disadvantage of Wigner-Ville transform is that the transformation is nonlinear, so when the signal components are much, the different components is easy to have the cross terms which causes the false image.

3.3.3 WAVELET TRANSFORM

The wavelet transform is put forward in the process of seismic data analysis by Morlet J. and Grossmann A in 1984. In the analysis of the seismic wave, it is found that the traditional Fourier transform is difficult to meet the requirements, so as to introduce the concept of wavelet [43,44].

When the signal is$f(t) \in L^2(R)$,the wavelet is$Wf(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt$.A very important part of this formula is $\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right)$. That is the generated continuous wavelet of $\psi(t)$.

In the practical application, the discretization of signal is needed. In the discretization, the equation changes to (5).

$$\overline{\psi}_{j,k}(t) = a_0^{\frac{-j}{2}} \overline{\psi}\left(\frac{t-ka_0^j b_0}{a_0^j}\right) = a_0^{\frac{-j}{2}} \overline{\psi}\left(a_0^{-j}t - kb_0\right) \quad a = a_0^j, b = ka_0^j b_0 \tag{5}$$

$$\overline{\psi}_{j,k}(t) = a_0^{\frac{-j}{2}} \overline{\psi}\left(2^{-j}t - k\right), a_0 = 2, b_0 = 1 \tag{6}$$

$$Wf(j,k) = \int_{-\infty}^{+\infty} f(t)\overline{\psi}_{j,k}(t)\, dt \tag{7}$$

The (6) is discrete dyadic wavelet function. The corresponding discrete wavelet transform coefficients are shown in (7).

The wavelet theory is based on the Fourier analysis and it is the development of Fourier transform. The traditional Fourier transform could not reflect the local characteristics of signal, but the wavelet transform can[45]. The wavelet has local characteristics in both time-domain and frequency domain. The orthogonal function system in wavelet analysis is used to generate the wavelet, which is based on the different shifts and scale changes. The wavelet analysis is like a mathematical microscope, which has the function of amplifying, reducing and translating. The function is equivalent to a set of equal bandwidth and central frequency band pass filter. Wavelet analysis uses short window in the high frequency, and the wide window is the low frequency, which provides a way for the real-time processing of sEMG signal[46,47,48,49,50].

4 CONCLUSION

The main extraction methods of the sEMG signal have their own characteristics, and it should be selected according to the actual situation . Time-domain method is applied to sEMG signal analysis from the beginning, but it is not stable and easy to be interfered. Then, the stability of the sEMG signal spectrum makes the frequency-domain method become the first choice in sEMG signal processing technology. As the representative of the time-frequency analysis method, wavelet transform combines the advantages of the time-domain and frequency-domain, which is quite potential in the EMG signal analysis. It becomes more and more popular. The complexity of EMG signal determines that the singular method may not make full use of the information in the research. The rapid development of computer technology and information processing technology provides the possibility for the comprehensive application to deal with the sEMG signal processing and lay the foundation for the further research. Also, it provides good opportunity to develop the upper limb rehabilitation robots.

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