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A Novel Feature Extraction Method for sEMG Signals using Image Processing

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***Abstract* – Several methods have been used for the feature extraction of surface electromyography (sEMG) signals, such as the integrated EMG (IEMG) in time domain and wavelet transform method in time and frequency domain. Because the EMG signals contain some inherent noise, the features extracted by these methods contain some incorrect values inevitably. According to the human vision, the image processing can be used to obtain the shape of sEMG signals. This paper focuses on the feature extraction of sEMG signals by calculating the geometric feature of sEMG signal using the pixel count method (PCM) in the image and calculating the textural feature using angular second moment (ASM) of gray level co-occurrence matrix (GLCM). The raw sEMG signals were recorded from three healthy subjects' biceps muscles. At the same time, the gray-scale image can be generated from the raw EMG signals. And then the proposed methods are used to calculate sEMG signals features from the gray-scale images. In the experiment, we classified the upper-limb voluntary movement into three motions and these motions are recognized by Back-propagation neural network (BPNN). For comparison, IEMG and wavelet packet transform (WPT) are also used to extract the sEMG features for motion recognition. The experimental results show that the proposed method is superior to the IEMG and WPT method.**

Index Terms* *–Image feature extraction, Surface Electromyography (sEMG), Image processing, Texture feature, Geometric features.

I. INTRODUCTION

Electromyographic signal (EMG) can be used to predict the intention of human's movement, since it is deeply related to the activation of motor muscle and human body's motion [1]. Several methods have been proposed these years for analyzing the EMG signals. In general, they can be separated into three types which are time domain, frequency domain and time-frequency domain [2][3]. Time domain method mainly includes Integrated EMG (IEMG), Mean Absolute Value (MAV), Root Mean Square (RMS), and so on. Frequency domain method mainly includes Fourier Transform (FFT), and so on. The wavelet packets method combines the time domain and frequency domain together, and it is a generalization of wavelet decomposition that offers a richer signal analysis [4][5]. However, the features of the time domain and frequency domain have always been unideal, which can hardly meet our demands. More intuitively, the EMG signals can be dealt as an image and extract features more efficiently based on image processing methods.

Image processing technology is growing fast these years, due to the promotion of computer's processing speed [6]. It is widely used in many applications, such as satellite remote sensing, fingerprint identification, geological survey, tracking management system and so on [7]-[9]. Generally the methods of image processing include image pre-processing, image enhancement or exacerbated, image transformation, image segmentation, and image identification. And in these methods, importance is the feature extraction from image segmentation [10]-[12]. And the image identification is based on the features measured after the image segmentation and classification. The images features include geometric features, shape features, color features and texture features, and in this paper, the image geometric features and texture features were mainly used.

In order to analyze the image of sEMG signal, two features which are the texture and geometric feature was choosed. An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image [13]. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image [14]. Usually texture includes the rough texture, silky texture and bumpy texture. In an image the rough texture has a large difference between max and min of the grayscale values. Silky would have little difference between max and min of the grayscale values. The difference between max and min changes with the shape of the sEMG signals. Some methods used to calculate the texture such as Haralick, R.M proposed gray level co-occurrence matrix (GLCM). In this paper, two statistical methods for feature extraction were used; one is using angular second moment (ASM) form GLCM. The other method is based on geometric features of the image. The image geometric such as a line, a plane, a sphere, or a generally smooth surface and more complex shape, sum the pixels of subjects was requested for calculating the features[15]. The features refer to the aspect of such as the location of the object in the image, the direction, perimeter and area. The PCM uses to calculate geometric features. The pixel counting method (PCM) is a method of estimating the area of the Mandelbrot Set and the location of its center of gravity [16]. The area applied for another feature extraction, because the area is a convenient objective measurement of the range of objects.

II. Proposed Methods for SEMG Signal Feature Extraction

In this section, two methods will be introduced to extract features from images' geometric feature and texture feature.

A. *The Proposed PCM Method*

In the geometric feature, the area calculation is the easiest method to count the total of pixels from the subject. According to the definition of Pixel Count Method (PCM), the sum of the pixels within the boundaries of the objects is calculated to be the area. The formula is as shown in (1)

$$PCM = \sum_{q=1}^{n}\sum_{p=1}^{m} T(\mathrm{i},\mathrm{j}) \tag{1}$$

where, T(i, j) is pixel counts.

B. *Gray Level Co-occurrence Matrix (GLCM)*

A co-occurrence matrix is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset.

Suppose an image I to be analyzed is rectangular and has matrix C defined over an $N_y \times N_x$ image I. Let $L_x = \{1,2,\cdots N_x\}$ be the numbers of row, $L_y = \{1,2,\cdots N_y\}$ be the numbers of column. The set $L_y \times L_x$ is the set of the elements of the image ordered by their row-column designations [17].

$$\begin{aligned} P(i,j,\delta,\theta) = \#\{ & ((\mathrm{k},\mathrm{l}),(\mathrm{m},\mathrm{n})) \in (\mathrm{L_x} \times \mathrm{L_y}) \\ & \times (\mathrm{L_x} \times \mathrm{L_y}) | \mathrm{k} - \mathrm{m} = 0, |\mathrm{l} - \mathrm{n}|, I(\mathrm{k},\mathrm{l}) = \mathrm{i}, \mathrm{I}(\mathrm{m},\mathrm{n}) = \mathrm{j}\} \end{aligned} \tag{2}$$

In (2) , # denotes the number of elements in the set. The matrix of relative frequencies P(i, j) with which two neighboring elements separated by distance δ (δ=1) occurs in the image, one with the gray level I and the other with gray level j.

GLCM is also called as Gray level Dependency Matrix. It is defined as "A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship" [18]. GLCM of an image is computed using a displacement vector δ, defined by its radius δ and orientation [18]. Fig.1 (a) is a 3×3 image with three gray-tone values from one to three. Four different directions are selected for gray level co-occurrence matrix calculation, i.e. θ = 0°, 45°, 90° and 135° respectively. Thus four gray level co-occurrence matrixes: G1, G2, G3, G4 are obtained from these four directions respectively. For example from (2), a Co-occurrence Matrix at $\theta = 0°$, $\delta = 1$ is shown in Fig.1 (b) [18][19].

One of the parameters from GLCM is called angular second moment (ASM), as shown in (3) [17]-[19]. In this paper, the equivalent expression with Fig.1(a) defines as θ=0° and δ=1, and three gray-tone values are from the subject of the image.

1	3	2
3	2	2
1	3	1

(a) 3x3 image with three gray-tone value 1-3

j \ i	1	2	3
1	0	0	2
2	0	1	0
3	1	2	0

(b) GLCM for θ=0°, δ=1

Fig.1 Matrix Elements and GLCM Matrix

$$\mathrm{ASM} = \sum_i \sum_j \left(\frac{P(i,j)}{R_H}\right)^2 \tag{3}$$

In (3), P(i, j) is the matrix of relative frequencies. R_H is a standardized constant with different sample image. Such that the P (i, j) is the six set of elements (as shown in Fig.1 (b)), generated from Fig.1 (a) and R_H is summation all of the pair of elements in this example it is 6.

C. *The Feature Extraction with PCM and GLCM*

In this paper, the sEMG data were obtained from the biceps muscle during the motion of upper limb flexion and extension. The data are used by a personal EMG filter box to generate the waveform on computer A. At the same time, the web camera is recording the waveform in the real time and display on the computer B with a cable USB the flowchart as shown in Fig.2. As shown in Fig.4, we defined the zone of EMG signal on the screen as α .

The pixel count method can reflect the change of the waveform of sample image's edge by extracting the values of the EMG graph's geometric feature. The waveform at different motion status has a relationship with the α 's area, and the area is calculated by using (1). For example: two kinds of EMG signals' images are got (as shown in Fig.3(a) and Fig.3(b)). These images are recorded from the biceps muscle which represent the static status and flexion motion respectively. The grayscale values of the α change from N_1 to N_x and the area of α is the sum of all of these grayscale numbers ranged from N_1 to N_x. During the upper limb motion, the α 's area is along with the contraction lever of the muscle. For example the area increases when the subject performs the flexion motion. In different motions, the different values of α 's area can be got. So the value of the α 's area as a feature of sEMG image were used.

On the other hand, among the different motion status, the texture of sEMG image is along with contraction lever of the muscle as well as the area. So the value of the texture can be regared as the feature. The ASM calculate by the GLCM has the ability to represent the uniformity of the distribution of the gray image. When the GLCM elements in distribution are more concentrated in the vicinity of the main diagonal, the distribution of the image gray is more evenly distributed in the

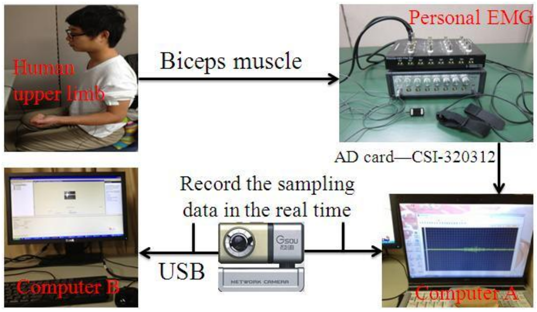
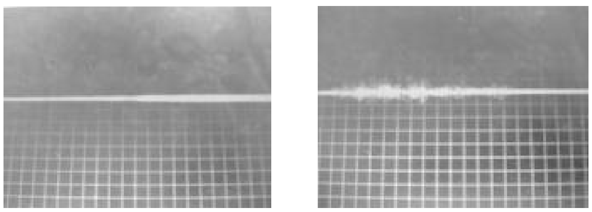


Fig.2 The flowchart of the feature extraction



(a) Image of sEMG signal when the limb keep relax (biceps muscle)

(b) Image of sEMG signal when doing the flexion motion (biceps muslce)

Fig.3 The different motion status of α 's area

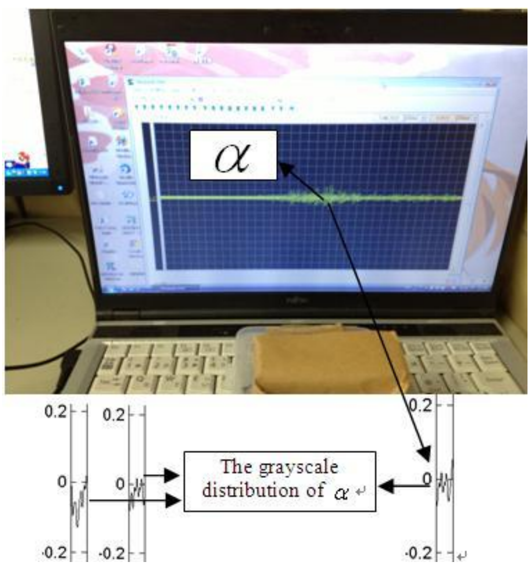


Fig.4 The difference of gray scale in subjects α

α , and images are rendered as smaller texture, and the value of the angular second moment is bigger. The features are calculated by (2) and (3), where P(i, j) is the set of the element with a and b (a, b are the range of pixels in the α) at horizontal direction. The ASM can be representative of the uniformity of the distribution of the α .

D. *The Comparison Methods*

The IEMG method and the wavelet packet transform for feature extraction are used for comparison.

Integrated EMG (IEMG) is defined as the area under the curve of the rectified EMG signal, that is, the mathematical integral of the absolute value of the raw EMG signal. And the formula is shown in (4)

$$IEMG = \sum_{n=1}^{n} |x_n| \tag{4}$$

where , x_n is the raw sEMG signal value; N is set to 200. To obtain the smooth signal, overlapped window is utilized during this procedure.

Wavelet packet transform (WPT) can decompose the signal into different frequency ranges for feature extraction. The basic formula is shown in (5). It is much smarter than filter banks which can be done by finding the "best tree" (the u2 and u3 are used to filter the raw sEMG signals) based on an entropy criterion[5]. Information in high frequencies can be analyzed as with in low frequencies in wavelet packet transform. Fig.5 shows the decomposition tree and the level of decompositions.

$$WT_x(a,b) = \frac{1}{\sqrt{a}} \int x(t)\psi^*(\frac{t-b}{a})dt = \int x(t)\psi^*_{a,b}(t)dt = \langle x(t), \psi_{a,b}(t) \rangle \tag{5}$$

In (5), a is positive and defines the scale and b is an arbitrary real number and defines the shift. The $\psi_{a,b}(t)$ is the mother wavelet.

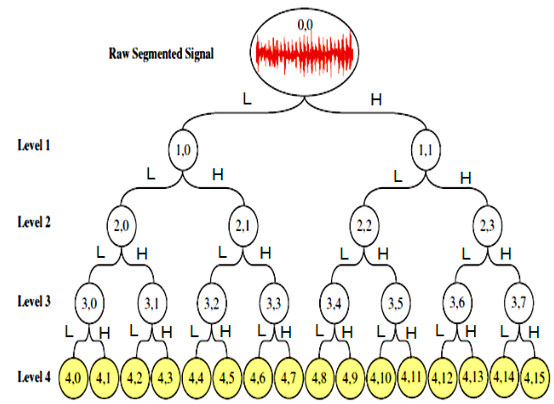


Fig.5 Decomposition tree and the level of decompositions

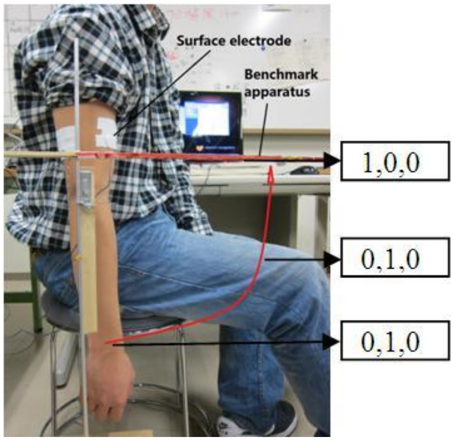
The BPNN will take the features calculated by using (4) and (5) as inputs, and then take training. The real time experimental results are compared with the proposed methods.

E. *Motion Recognition*

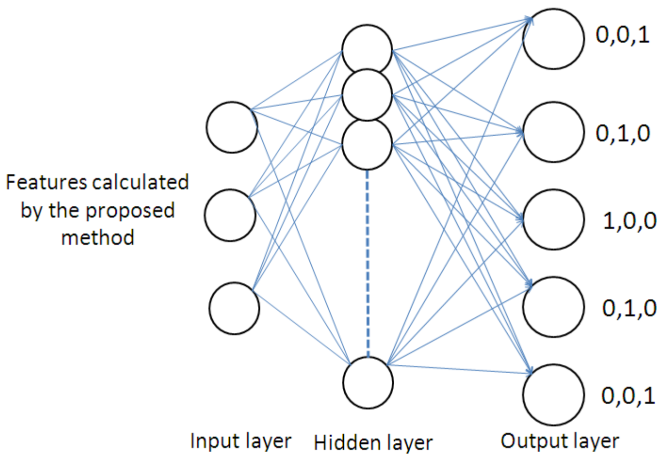
In the experiment, the volunteers are asked to perform the same motion for three times. The upper-limb voluntary movements are classified into three motions and these motions are recognized by Back-propagation neural network (BPNN). The BPNN has one hidden layer and 20 nodes. The inputs are the features of the grayscale images calculated via the proposed methods and comparison methods respectively. And the output matrix is the combination of the quantification of the upper limb movement classification. As shown in Fig.6 (a), the relaxed position is defined as (0, 0, 1), the flexion position is defined as (1, 0, 0) and the extended position is (0, 1, 0).

TABLE I
The specification of web-camera

Default Format	Frame Rate	Sampling numbers	Acquisition time (s)
120x160	30	200	7



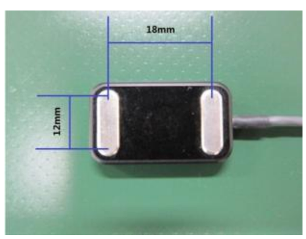
(a) The unique combinations of zeros and one presenting for different motions



(b) Structure of BPNN

Fig.6 Corresponding BPNN with forearm moves in the experiment

(a) The personal EMG filter box



(b) The surface electrode

Fig.7 The sEMG signals extraction devices

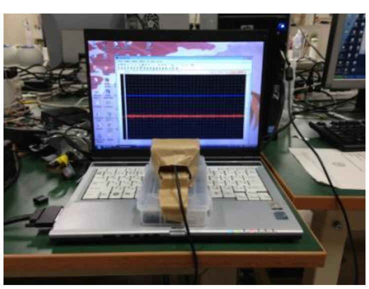


Fig.8 The image acquisition device

III. EXPERIMENTAL RESULTS

A. The Experiment Setup

A commercial filter box (Osaka Electronic Device Ltd. Japan) is used as shown in Fig.7 (a) for the preprocessing of the data. These data are sampled by an AD card (CSI-320312 Interface. Co. Japan) with the sampling rate of 1000Hz. The electrode is 18 mm long and 12 mm wide, as shown in Fig. 7 (b). The monitoring the activities of sEMG is from the biceps brachii [20].

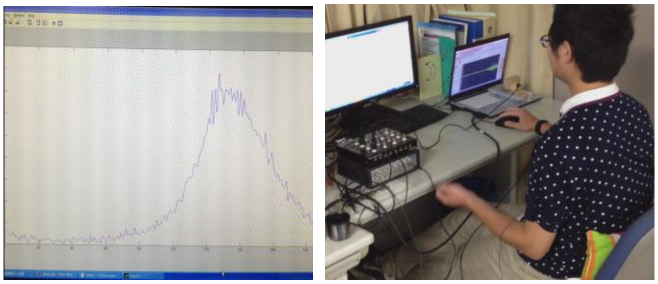
A web-camera is fastened in front of the computer A as shown in Fig.8 and the property is shown in Table I. The computer B is used to display the continuous acquisition images. The position of the camera is well set in order to make the camera focus on a certain range of the screen. At the same time, the color images were translated into the grayscale images. Then the computer B will calculate the features using PCM and GLCM respectively for feature extraction as shown in Fig.9. The user interface was programmed using MATLAB (MathWorks Co. USA) via a communication from the custom interface to the commercial software running on the computer B with a 2.66GHz quad-core processor (Intel Core Q8400) and 2GB RAM.

B. The Experiment Results

Three healthy volunteers, who are all male, (information as shown in Table II), participated in the experiment. Before sticking the electrodes the volunteer's skin was shaved and cleaned with soap and alcohol for reducing the skin impedance. And then the electrode was aligned parallel to the muscle fibres of the bicipital muscle. The volunteers were asked to perform the motion of flexion and extension, where there were 2s in the relaxed position, 3s in the flexion position and 2s in the extended position. The PCM and GLCM methods are used to calculate the features of three groups of obtaining images. Finally, the BP neural network is used for upper limb motion recognition.

Fig.10 and Fig.11 depict the calculation results of the EMG features extracted by the proposed two methods, PCM and ASM, respectively. The values calculated by PCM and ASM can indicate the status of flexion and extension motion. For example, from sampling number 45 to 85 (1.68s to 3.19s) , subject performed the motion of upper limb flexion and the features increased gradually. From sampling number 130 to 170 (4.88s to 6.38s) , subject performed the motion of upper limb extension and the features decreased gradually.

Three sets of features from volunteer A, B and C were identified by BPNN respectively and the recognition rate calculated by PCM is shown in Fig.12 (a) (b) (c). For comparison the IEMG and WPT methods were implemented to extract features. These features were also sent to the BPNN for motion recognition and the comparison results are shown in table III.



(a) Display of user interface (b) Experimental procedure of upper limb movement

Fig.9 The experiment in real-time with Matlab environment

TABLE II
Time and motion with different volunteers

Time (s)	Motion	Height (cm)	Weight (kg)	Age
7	Flexion& extension	177	70	25
7	Flexion& extension	175	72	25
7	Flexion& extension	172	65	27

The time consuming with PCM is 7.39s and the time consuming with GLCM is 7.54s. The processing time for generating each grayscale image is about 36 ms, because the frame rate of the web camera is about 30 and there is a small time-delay in the computer hardware. The time consuming of feature extraction with a PCM method for each gray scale image is about 0.9 ms and using GLCM method consumes about 1.2 ms. Because of the computational complexity of GLCM, it takes more time than PCM method, but it doesn't affect the experiment in real-time.

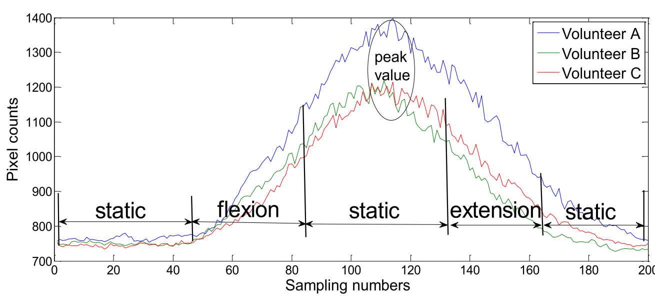


Fig.10 The features calculated by PCM method with different volunteer

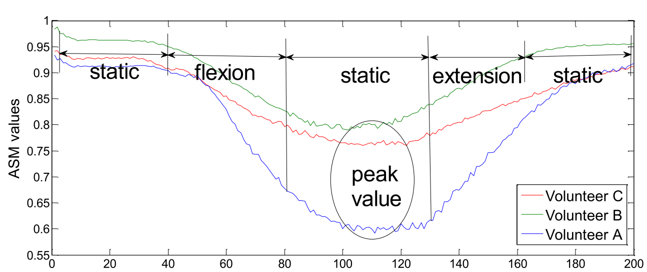
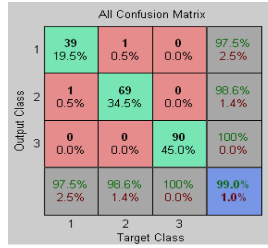
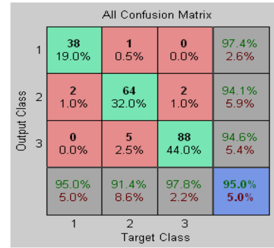


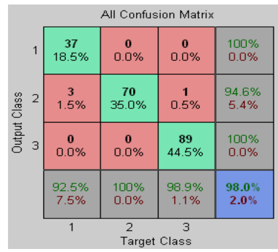
Fig.11 The feature calculated by GLCM with different volunteer



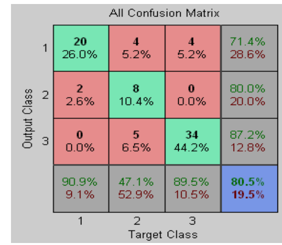
(a) Recognition rate of A (PCM)



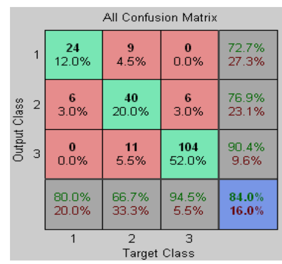
(b) Recognition rate of B (PCM)



(c) Recognition rate of C (PCM)



(d) Recognition rate of A (IEMG)



(e) Recognition rate of A (WPT)

Fig.12 motion recognition rate

TABLE III
The comparison of previous studies

	IEMG	WPT	PCM	ASM
Recognition rate	80%	85%	96%	95%
Time (s)	7.4	7.4	7.5	7.5
Training numbers	800	800	800	800

IV. Discussion

The feature extraction is important in our study. In this paper, the EMG signals are treated as images. The first step is image pre-processing. The web-camera is used to collect a gray-scale image of the EMG signals for the purpose of detecting the gray level range of the α (as shown in Fig.3). The extracted values were from 170 to 250 in the experiments. Light intensity has given rise to this large difference. During the experiment, the light intensity affectting the gray uniform distribution is noticed. To solve this problem a mean filter was used for image processing during the image acquisition. The range of gray-scale values is from 240 to 250 after filtration. So the mean filter can effectively improve the accuracy of feature extraction for image pre-processing. And in the comparison experiments, two conventional methods i.e. the IEMG and the WPT are implemented for evaluating the efficiency of our proposed methods. All the external environment of the experiments were the same, and the input data were all from the raw sEMG.

V. CONCLUSIONS AND FUTURE WORK

In this paper, two image processing methods, i.e. PCM and ASM in the GLCM, are used for the EMG signal feature extraction. The PCM is used to calculate the image geometric feature and the ASM is used to calculate image texture feature. And then experiments of motion recognition used Back-propagation Neural Networks were carried out to evaluate the efficiency of the proposed methods. IEMG and WPT methods are also used for comparison. The experimental results are acceptable. The motion recognition rate of volunteer A is the highest in the three subjects. It is possible that the range of motion from volunteer B and volunteer C are not deep enough. On the other hand, the processing time of feature extraction using the PCM method or GLCM method is very short. This result fits with our expectations, and it can be considered as real-time processing.

The gray value is affected by light intensity severely. In this paper, the light intensity is constant. In the future, we want to obtain a better feature under different light intensity conditions. And then we want to do the multi-movement with image processing. The method will be applied to clinical medicine and rehabilitation.

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REFERENCES

[1] Z. Song and S. Guo, "Design Process of a Novel Exoskeleton Rehabilitation Device and Implementation of Bilateral Upper Limb Motor Movement," Journal of Medical and Biological Engineering, Vol. 32, No. 5, pp. 323-330, 2012.

[2] Z. Song, S. Guo, M. Pang and S. Zhang, "Recognition of Motion of Human Upper Limb using SEMG in Real Time: Towards Bilateral Rehabilitation," Proceedings of 2012 IEEE International Conference on Robotics and Biomimetics, pp.2050-2055, 2012.

[3] Z. Song, S. Guo, "Study on Impedance Generation Using an Exoskeleton Device for Upper-Limb Rehabilitation," Proceedings of 2012 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, pp.281-286, 2012.

[4] M. Pang, S. Guo, and Z. Song, "Study on the sEMG driven Upper Limb Exoskeleton Rehabilitation Device in Bilateral Rehabilitation," Journal of Robotics and Mechatronics, Vol. 24, No. 4, pp. 585-594, 2012

[5] S. Guo, S. Zhang, Z. Song, M. Pang, Y. Nakatsuka, "Preliminary Study on Upper Limb Movement Identification Based on sEMG signal," Proceedings of the 2012 ICME International Conference on Complex Medical Engineering, pp. 683-688, 2012.

[6] H.P. Huang and C.Y. Chen "Development of a myoelectric discrimination system for a multi-degree prosthetic hand," IEEE International Conference on Robotics and Automation, Vol. 3, pp. 2392-2397, 1999.

[7] K. Englehart and B. Hudgins. "A robust, real-time control scheme for multifunction myoelectric control," IEEE Transactions on Biomedical Engineering, Vol. 50, No.7, pp. 848-854, 2003.

[8] S. Sharma and G. Kumar, "Wavelet analysis based feature extraction for pattern classification from Single channel acquired EMG signal," Elixir Online Journal , Vol. 50, pp.10320-10324, 2012.

[9] Z. Zhao, S. Guo, and N. Xiao, "Development of an FHMA-based Underwater Acoustic Communications System for Multiple Underwater Vehicles," International Journal of Robotics and Automation, Vol. 3, No. 2, pp. 61-76, 2012.

[10] J. Guo, S. Guo, N. Xiao, and Baofeng Gao, "Virtual Reality Simulators based on a Novel Robotic Catheter Operating system for Training in Minimally Invasive Surgery," Journal of Robotics and Mechatronics, Vol. 24, No. 4, pp. 649-655, 2012.

[11] B. Gao, S. Guo, N. Xiao and Jin Guo, "Design of the Virtual Reality based Robotic Catheter System for Minimally Invasive Surgery Training," Proceedings of the 2012 IEEE International Conference on Automation and Logistics, pp.622-627, 2012.

[12] B. Krill and A. Ahmadb, "An efficient FPGA-based dynamic partial reconfiguration design flow and environment for image and signal processing IP cores," International Journal of ScienceDirect on Signal processing, Vol.25 No.5, pp.377-387, 2010.

[13] H.B.Kekre, Tanuja K. Sarode, Sudeep D. Thepade, "Image Retrieval using Color-Texture Features from DCT on VQ Codevectors obtained by Kekre's Fast Codebook Generation," International Journal on Graphics, Vision and Image Processing, Vol.9, No.5, pp.1-8, 2009.

[14] H. B. Kekre, Sudeep D. Thepade, Tanuja K. Sarode and Vashali Suryawanshi, "Image Retrieval using Texture Features extracted from GLCM, LBG and KPE," International Journal of Computer Theory and Engineering, Vol. 2, No. 5, pp.695-700, 2010.

[15] Atsushi Yamashita, Atsushi Kawarago, Toru Kaneko Kenjiro, T. Miura, "Shape Reconstruction and Image Restoration for Non-Flat Surfaces of Documents with a Stereo Vision System," International Conference on Pattern Recognition, Vol.1, pp.482-485, 2004.

[16] K. Michielsen, H. De raedt, "Integral-geometry morphological image analysis," International Journal of ScienceDirect on Physics Reports, Vol.347, pp.461-538, 2001.

[17] Haralick R. M., Shanmugam K., Dinstein Its'Hak, "Textural features for image classification," IEEE Transactions on systems,man and cybernetics, Vol.SMC-3, No.6, pp.610-621, 1973.

[18] Y. Xu and S. Huang, "Scale-space texture description on SIFT-like textons," Computer Vision and Image Understanding, Vol.116, No.9, pp.999–1013, 2012.

[19] S. Sreehari Sastry and T. Vindhya Kumari, "Transition Temperatures of Thermotropic Liquid Crystals fromthe Local Binary Gray Level Cooccurrence Matrix," Advances in Condensed Matter Physics, Vol.2012, pp.1-9, 2012.

[20] M. Pang, S. Guo, Z. Song and S. Zhang "A Surface EMG Signals-based Real-time Continuous Recognition for the Upper Limb Multi-motion," International Conference on Mechatronics and Automation, pp. 1984-1989, 2012.