Design of A Virtual Reality System based on Wireless Surface Electromyography Signals

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Abstract

A virtual reality real-time control system based on wireless surface electromyography (sEMG) is designed. The system consisted of four parts: real-time myoelectricity signal detection and segmentation, feature extraction, classification identification and control instruction. Four kinds of action sEMG control in virtual kitchen were completed. The experimental results showed that this system could perform the real-time control of virtual kitchen action, and the average online identification accuracy was 90.31%. The system can be used for muscle rehabilitation training, and provide immersive virtual kitchen scene.

Key words: surface electromyography; virtual reality; feature extraction; real-time control

Introduction

The bioelectrical signals of the human contain abundant information, such as perceptual information and physiological states. At present, the bioelectrical signals such as electroencephalogram (EEG), electromyography (EMG), and electrocardiogram (ECG) are widely concerned [1]. The surface electromyography (sEMG) signal generated by a kind of motion potential may be excited by a moving unit. This motion potential is transmitted along the muscle fiber to the surface of the skin and recorded by the electrodes [2]. The sEMG is closely related to muscle activity and exercise status, whose amplitude is 0.01 mV to 10mV [3]. The energy of sEMG mainly varies between 20Hz and 500Hz [4]. The human-computer interface (HCI) is a new human-machine information exchange and control technology, which does not rely on conventional information interaction. The muscle-computer interface (MCI) is a novel HCI technology. The MCI can apply the sEMG to identify the type of human motion and convert the sEMG signal into an input command. The sEMG is widely used in the myoelectricity signal detection, which is the first choice for the MCI because of its non-invasive, real-time and easy operation [5]. The sEMG has important significance in clinical diagnosis, rehabilitation medicine and intelligent prosthetic control [6]. In recent years, the sEMG signal has been used in sign language gesture recognition, rehabilitation system, virtual reality (VR) game control and wearable device [7].

In this study, the virtual kitchen was combined with the MCI, and the sEMG signals were transmitted to the computer using wireless transmission. The users can interact with virtual kitchen without using other interactive devices such as a mouse or a keyboard.

System framework

The overall framework of the system is shown in Fig.1. The system was designed with sEMG acquisition module, software control module and VR environment module. The sEMG acquisition module used the portable wireless system Trigno that was produced by DELSYS Corporation. The software control module consisted of real-time myoelectricity signal detection and segmentation, feature extraction, classification identification and control instruction. The VR environment module drived to perform different motions according to instructions provided by the classification in virtual kitchen.

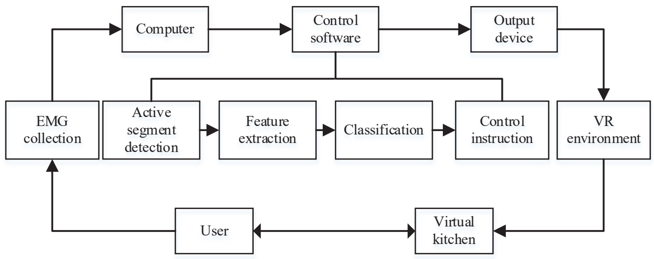


Fig.1 VR system framework based on wireless sEMG signals

Analysis methods

A. Detection

The algorithm used in the active segment detection is the combination of mean square value and moving average window [31]. In order to obtain the instantaneous average energy $\mathrm{sEMG_M}$, the raw sEMG signal $\mathrm{sEMG_k}$ is squared. i is the label of current sEMG signal. $\mathrm{sEMG_M}$ is defined as

$$\mathrm{sEMG_M(i)} = [\mathrm{sEMG_k(i)}]^2 \quad (1)$$

A moving window is used to calculate the energy average of window length $\mathrm{sEMG_{ma}}$. N is a fixed length, which can be adjusted. $\mathrm{sEMG_{ma}}$ is defined as

$$\mathrm{sEMG_{ma}(i)} = \frac{1}{\mathrm{N}} \sum_{\mathrm{j=i}}^{\mathrm{i+N}} \mathrm{sEMG_M} \quad (2)$$

The sEMG signal is judged by comparing $\mathrm{sEMG_{ma}}$ with a fixed threshold TH. The sampling points greater than or equal to the threshold are selected, and the sampling points less than the threshold are set to zero. In this way, the starting point and ending point of active segment are chosen, that is

$$\mathrm{sEMG}_{rec}(i) = \begin{cases} \mathrm{sEMG}_{ma}(i) & \text{if } \mathrm{sEMG}_{ma}(i) \geq \mathrm{TH} \\ 0 & \text{if } \mathrm{sEMG}_{ma}(i) < \mathrm{TH} \end{cases} \quad (3)$$

Fig.2 shows sEMG waveforms before and after preprocessing.

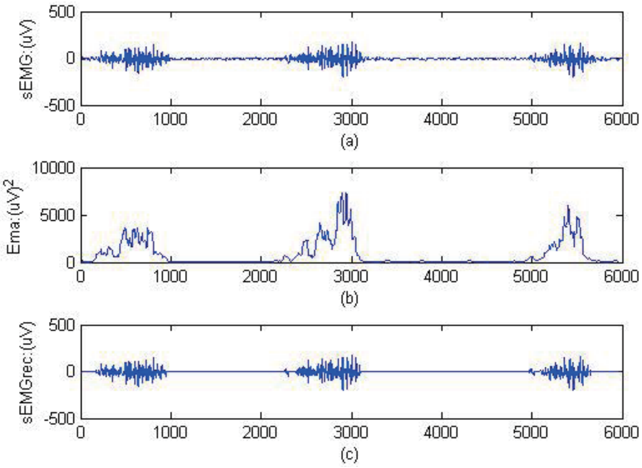


Fig.2 sEMG waveforms before and after preprocessing
(a) Raw signal; (b) Instantaneous energy signal; (c) Segmented signal

B. Feature extraction

The time-domain methods such as mean absolute value (MAV), root mean square (RMS) and standard deviation (SD) are usually used in the feature extraction of the sEMG [8].

The autoregressive (AR) is a linear regression model that can be used to describe the sEMG signal, that is

$$\mathrm{sEMG}(k) = w(k) - \sum_{m=1}^{p} a_m \mathrm{sEMG}(k-m) \quad (4)$$

$\mathrm{sEMG}(k)$ represents the sampling value of current sEMG. $w(k)$ is the input noise value. p is the order of the model. a_m is the m-th coefficient of the model, which can be used as the feature for the classification of sEMG signals. When p ranges from 3 to 6, the best classification results can be obtained. The order of AR model is the important factor for describing the sEMG signal correctly. In this study a four order AR is optimal for the sEMG signal [8].

The sEMG signal is a kind of non-stationary signal. The wavelet method can provide all information of the signal sequence, especially for the degree of signal variation. This feature is suitable for dealing with unstable signal such as the sEMG signal. The discrete wavelet transform is as follows

$$g(t) = \sum_{k=-\infty}^{\infty} c(k)\varphi_k(t) + \sum_{j=0}^{\infty}\sum_{k=-\infty}^{\infty} d(j,k)\psi_{j,k}(t) \quad (5)$$

where $g(t)$ is a time series signal, $\varphi(t)$ is a scaling function, and $\psi(t)$ is a wavelet function.

The signal is decomposed into three layers using orthogonal wavelet basis function sym3, and the singular values of wavelet coefficients at each layer are extracted as the feature vectors.

C. Classification

The support vector machine (SVM) is a supervised machine learning method. The raw spatial data are converted to higher dimensional space, and linearly separable dataset is obtained. The dataset is separated into two classes by a linear hyperplane. The maximum-margin is defined according to the position of two nearest points that belong to different classes. The new dataset can be classified by the maximum-margin hyperplane. The advantage of the SVM algorithm is that it can solve the problems of small sample, nonlinear and high dimension.

D. Interface

The control interface for virtual kitchen is designed on the basis of MATLAB platform using a graphical user interface (GUI). The interactive interface is shown in Fig.3. The design details are as follows.

(1) Button control: these buttons control the display of the sEMG signals including virtual kitchen start, feature extraction, classification and motion control.

(2) Real-time sEMG waveform display: the raw sEMG waveform is displayed.

(3) Feature extraction result display: the feature distribution of myoelectricity signal is displayed.

(4) Classification result display: four motions are identified effectively.

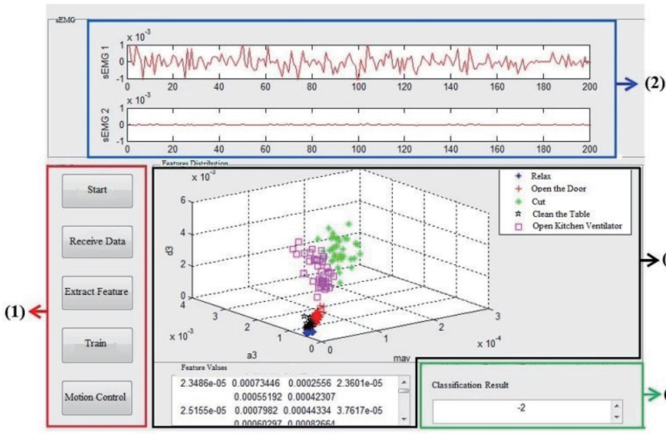


Fig.3 Virtual kitchen control interface

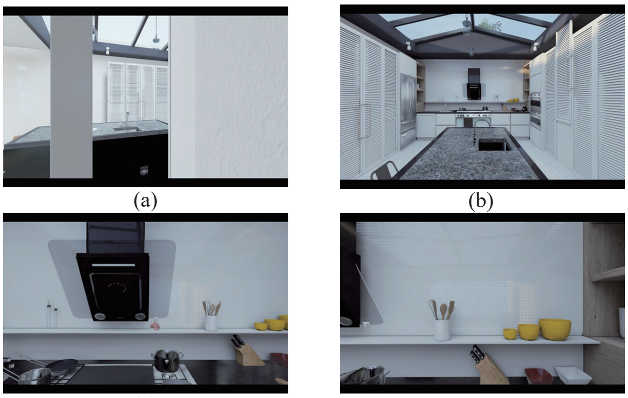
Experimental results

The sEMG data used in this study were collected from four subjects. Two males and two females, 21 to 25 years old, participated in the experiment. All subjects had no motor function and neurological diseases in the last six months. They understood the experiment protocol. Two sEMG electrodes were respectively placed on flexor carpi ulnaris muscle and extensor carpi ulnaris muscle. They were used as channel 1 and channel 2 for dual-channel sEMG signal acquisition. Four motions included wrist flexion, wrist extension, fisting and palm extension.

The MAV and wavelet transform were chose as the features, and the dual-channel features were combined to obtain six-dimensional feature values. The AR coefficients were added to the above features, but the classification results were not improved. The sEMG data of four subjects were used to train the SVM classifier model. The wrist flexion represented the motion of cleaning the table, the wrist extension represented the motion of opening kitchen ventilator, the fisting represented the motion of opening the door, the palm extension represented the motion of cutting the food.

Fig.4 Real-time control with dual-channel sEMG

Four subjects completed real-time control experiment. The control scene is shown in Fig.4. The kitchen interfaces are shown in Fig.5. This system can effectively identify real-time sEMG signals of four motions, and the average classification results are shown in Fig.6. The accuracy for opening the door is 87.5%, 91.25% for cleaning the table, 93.75% for cutting the food, and 88.75% for opening kitchen ventilator. The average accuracy of four motions is 90.31%.



(a) (b) (c) (d)

Fig.5 Kitchen motions
(a) opening the door; (b) cleaning the table; (c) opening kitchen ventilator;(d) cutting the food

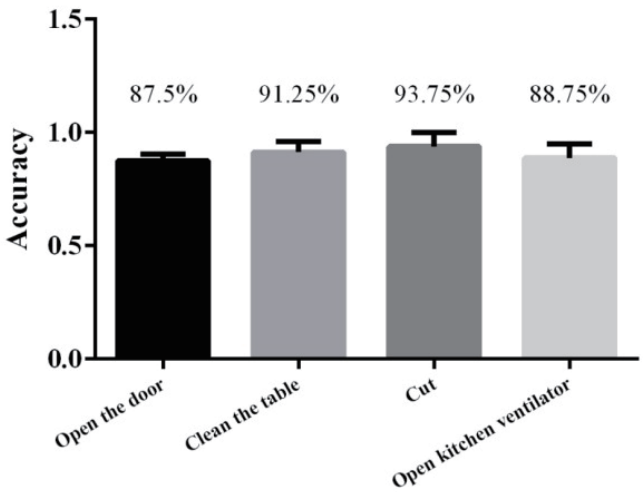


Fig.6 Accuracy comparisons for four motions

Conclusion

The real-time control of virtual kitchen using the sEMG signals was completed in this system. The sEMG signals from flexor carpi ulnaris muscle and extensor carpi ulnaris muscle were collected and segmented. The MAV and singular values of wavelet coefficients were selected as sEMG features. The two features were combined. The SVM classifier was used to identify real-time sEMG signals in this system. Finally, the control of four virtual kitchen motions was completed by the dual-channel sEMG signal, and the average accuracy was 90.31%. This system can be used for the patients who need muscle rehabilitation training. The virtual kitchen is closer to the real life scene. The patient can complete the rehabilitation training by cooking in virtual kitchen. This study not only adds the fun to the patient, but also enables the patient to actively participate in rehabilitation training. It is of positive significance to the rehabilitation of patients, which can provide an assessment analysis of the muscle recovery.

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