A New Electrode System for Hand Action Discrimination

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Abstract

Sign languages are composed of hand and finger actions and are combinations of the flexion and extension of fingers, wrist, forearm, and arm. Thus, an EMG-based hand action identification system is proposed in this study. The purpose of this system is to identify a sufficient amount of basic hand actions in order to use this information to recognize more complicated sign language in the future. This system uses active electrodes placed around the forearm to collect EMG signals from muscle groups of the forearm. To avoid miss-identification of the action period due to noise and artifacts in the EMG signals, in this study a multi-thresholds method is proposed. Features extracted from the new EMG electrode system are inputted to a back-propagation ANN identification system for hand action discrimination. Eleven subjects were recruited for this study. The results indicate that when six features from seven EMGs were input into the ANN, the average discrimination rate was 93.1%. When one feature from each channel was used, the discrimination rates ranged from 73.2% to 90.4%. On the other hand, when two features with the highest discrimination rate in the previous results were selected, the average discriminative rate increased to 86.9% and 90.3%. However, the current system cannot detect movements of the upper arm. Additionally, due to the large between-subject variations, the system must go through the training sequence before every use. Nevertheless, the results indicate that, with the ring electrode system and multi-thresholds method, the proposed system does provide high discriminative ability for the actions of fingers, palm, wrist, and forearm.

***Keywords*:** Hand action, Active electrode, Artificial neural network

Introduction

There are approximately sixty thousand persons with hearing impairments in Taiwan, most of whom communicate with each other by means of sign language. However, the general public, who has never trained with sign language, is unable to understand, so handwriting is generally used to resolve this communication difficulty. However this is inefficient and constricted by the circumstances. For example, while standing or walking, it is not possible to write. Therefore, if we could change sign languages into audible speech, that would resolve this difficulty. On the other hand, electromyography (EMG) patterns have previously been used to identify hand actions. For example, EMG patterns from amputees have been used in several studies to provide reliable and accurate systems to control and assist prosthetic devices [1, 2]. In addition to prosthesis control, EMG has also been used to identify the action of hands and legs during functional electrical stimulation (FES) [3]. These studies demonstrate that hand actions, such as extension of the forearm, hand opening and grasping or bending of the finger can be identified using EMG signals from muscle groups that are not directly corresponding to that particular action. In most of these studies, artificial neural networks (ANN) have been successfully used for hand action identification.

Since, sign languages are composed of hand and finger actions and are combinations of the flexion and extension of fingers, wrist, forearm, and arm. Thus, an EMG-based hand action identification system is proposed in this study. This system uses active electrodes placed around the forearm to collect EMG signals from muscle groups of the forearm. The proposed electrode system is design to avoid the drawbacks of sensitivity to electrode displacement in previous studies. On the other hand, it has been demonstrated that the discrimination rate is highly dependent on the signal processing techniques that are used to extract features from the EMG signal. Thus, a new signal processing method is proposed to increase the reliability of feature extraction. Additionally, features extracted from the new EMG electrode system are inputted to a back-propagation ANN identification system for hand action discrimination. The purpose of this proposed system is to identify a sufficient amount of basic hand actions in order to use this information to recognize more complicated sign language in the future.

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Background

Kuribayashi et al reported a system using surface EMG signals and back propagation ANN for prosthesis control in 1993 [4], using absolute value and integration of EMG signals. This system can identify six hand actions, including relaxation, hand opening and closing, palmar flexion and dersiflexion, wrist pronation and supination, with the highest recognition rate of 95.5%. On the other hand, Fukuda et al used multiple surface EMG electrodes and a neural network to construct a robotic manipulator control system [5]. By additional on-line training technique, a 100% recognition rate can be achieved for six hand actions including extension, flexion, pronation, supination, hand open and hand close. In 2000, Huang and his collogues reported a digital signal processor based prosthesis control system and compared the effect of combining different EMG features on the recognition rate [6]. It was found that by combining the integral of EMG (IEMG), waveform length (WL), variance (VAR), zero crossing (ZC), Willison amplitude (WAMP) and parameters of 4-th order autoregressive model, after on-line training, an 87.5% recognition rate can be achieved.

Results of these experiments indicate that most of the forearm action can be identified by a system consists of surface EMGs and a neural network. However, there are still some drawbacks and shortcoming in these studies. First, all these researches and most of other studies required EMG electrodes to be placed on designated locations for signals collection, which could not be easily done outside the laboratory. Second, the discrimination rates can be achieved only for hand actions involve large muscle groups, and no study to identify different finger actions using surface EMG electrodes placed on the forearm has been conducted. To overcome these problems, a new electrode system is needed that can be worn without concern for the exact position of each electrode. Additionally, this electrode configuration should permit acquiring EMG signals from all the muscle groups in the forearm. Although EMG signals are know to be different in morphology and amplitude when the electrode placements are different, it is also known that the surface EMG is a combination of action potential of motor units near the electrode. In addition, numerical studies have been conducted to resolve the source localization in surface EMG [7]. Thus, it is assumed that with sufficient amount of surface EMG signal, all the necessary information for discriminating hand actions is contained within these EMG signals, and only the learning ability of ANN is necessary to resolve it.

Method

Electrode system

Active electrodes offer advantages such as reduced noise and high signal to noise ratio over the traditional passive electrode [8]. Most active electrodes provide strip, dot, or concentrated circle for signal inputs and differential amplification. The distant between two differential inputs affects the sensitivity of the electrode, and the longer the distance the more sensitive the electrode is [9]. On the other hand, the size of the electrode has an effect on the quality of acquired signal. For a large electrode the summation effect of individual motor unit is more apparent. Thus, a large active electrode provides EMG signal with larger amplitude. However, the drawback of a large electrode is that it is very difficult to secure onto the surface.

To acquire EMG signals from subjects when they are doing hand and finger actions, traditionally, multiple electrodes need to be placed on all the corresponding muscle groups. This process of placing electrodes is time-consuming and requires detailed knowledge of human anatomy. Additionally, some of the muscle group are closely together that make the acquisition of EMG signal from a single muscle group using surface electrodes almost impossible. To overcome these problems, a system is proposed by making active electrodes as small as possible and placing a large amount of these electrodes on the forearm in order to acquire all the EMG signals during hand actions. On the other hand, to be feasible for use outside the laboratory, the electrode system must be easy to apply. Thus, it is proposed to arrange multiple active electrodes around the forearm in a ring faction.

A 2cm-by-1cm active electrode is designed with two 3mm metal strips fabricated at the two ends on one side of the electrode. These two metal strips act as the two sensing electrodes. Consequently, this active electrode provides differential EMG signals with constant electrode distance. The amplification circuit, fabricated on the other side of the electrode, is composed of an instrumentation amplifier, a differentiator and a Butterworth low pass filter. This active electrode provides 68dB gain and 10 to 500Hz bandwidth. Seven active electrodes are attached to a magic tape to form the ring electrode system.

EMG signal processing

A total of 11 hand actions are defined and studied in this study. Four of them are defined according to previous studies, including fist flexion up and down, pronation and supination. Seven are newly defined finger actions including extension of the index finger, extension of index and middle fingers, extension of thumb and little fingers, extension of thumb and index fingers, extension of all fingers except the thumb and extension of all five fingers. Based on the study of Huang et al, six EMG features are extracted from the EMG signal including IEMG, WL, VAR, slope sign change (SSC), ZC and WAMP. All these features are selected for their ease in computation. They are defined as:

$$IEMG = \sum_{k=1}^{N} |x_k| \tag{1}$$

$$WL = \sum_{k=1}^{N} |\Delta x_k|, \text{ where } \Delta x_k = x_k - x_{k-1} \tag{2}$$

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N} x_k^2 \tag{3}$$

$$ZC = \sum_{i=1}^{N} [\operatorname{sgn}(-x_k \times x_{k+1}) and |x_k - x_{k+1}| \geq 0.02],$$

$$\text{where } \operatorname{sgn}(X) = \begin{cases} 1, & if \quad x > 0 \\ 0, & otherwise \end{cases} \tag{4}$$

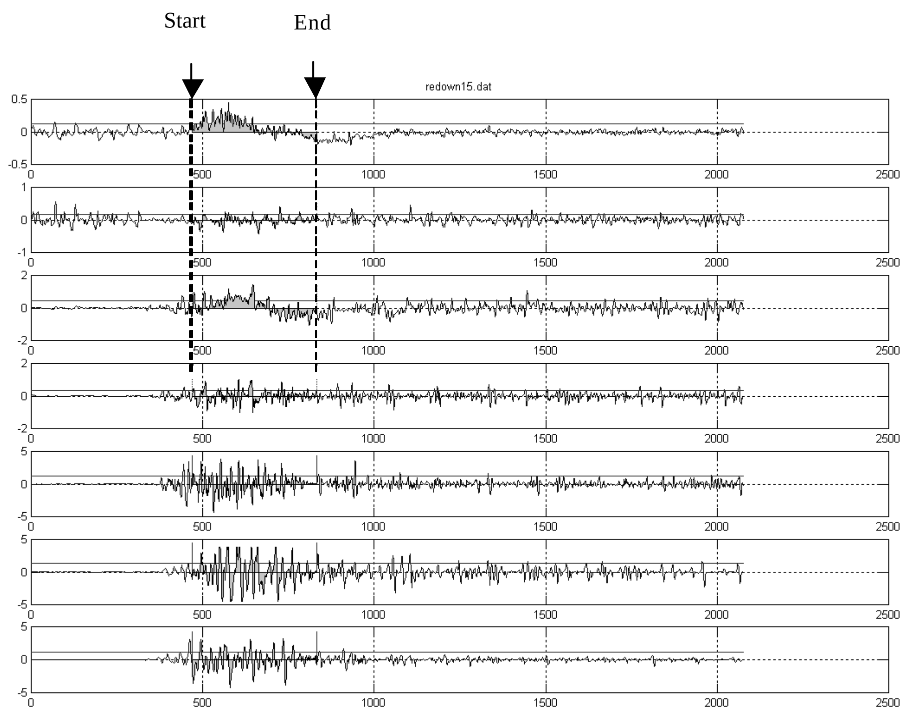

Figure 1. Determination of start and ending times of hand action period. During the recognition period, EMG signals are normalized and compared with corresponding thresholds. When two or more EMG signals exceed their corresponding threshold, it is marked as the beginning of one action. After the beginning of action, when six or more EMG signals are below the corresponding threshold, it is marked as the end of action.

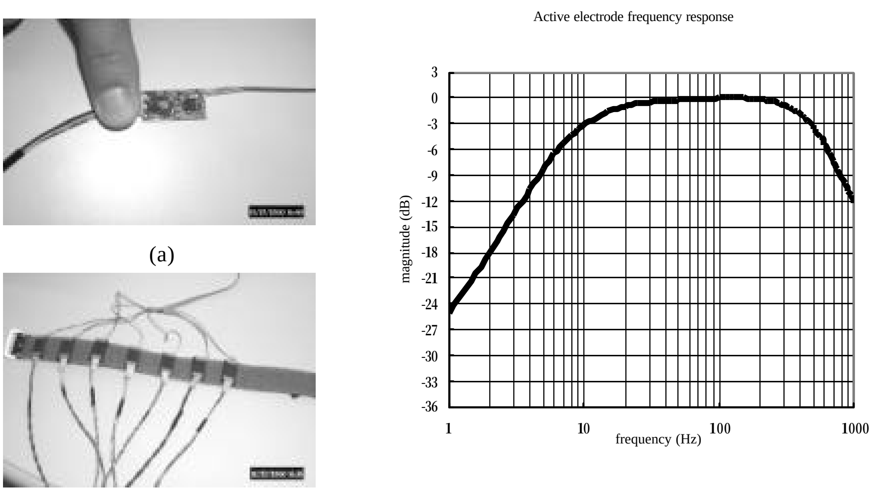

Figure 2. (a) The active electrode, (b) the ring electrode system and (c) a typical frequency response of an active electrode.

$$\text{SSC} = (x_k - x_{k-1}) \times (x_k - x_{k+1}) \geq 0.03\,,\ for\ k = 1,\ldots,N \quad (5)$$

$$WAMP = \sum_{i=1}^{N} f\left(\left|x_k - x_{k+1}\right|\right),$$

$$\text{where } f(x) = \begin{cases} 1, & if \quad x > 0.3 \\ 0, & otherwise \end{cases} \quad (6)$$

In order to correctly recognize hand actions, it is necessary to identify the beginning and end of action periods from continuously recorded EMG signals. To avoid miss-identification of the action period due to noise and artifacts in the EMG signals, in this study a multi-thresholds method is proposed. First, during the training period, while subject is doing designated actions, thresholds and normalization factors for each EMG channel are established, based on the absolute value of EMG signal. Then, during the

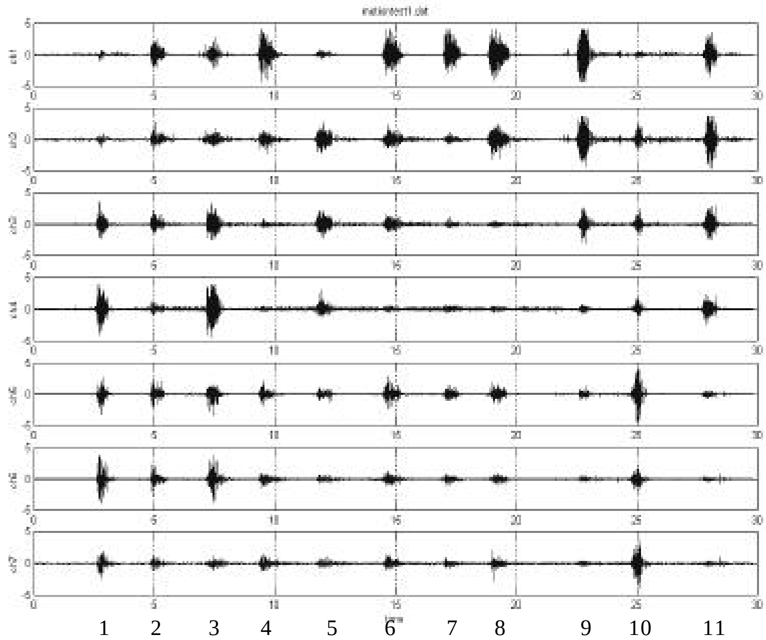

Figure 3. EMG signals that were acquired using the ring electrode system. Where (1)-(11) represent hand action flexion down, extension of thumb and little fingers, extension of index and middle fingers, extension of all five fingers, extension of thumb and index fingers, extension of the index finger, extension of all fingers except the thumb, pronation, supination and flexion up, respectively.

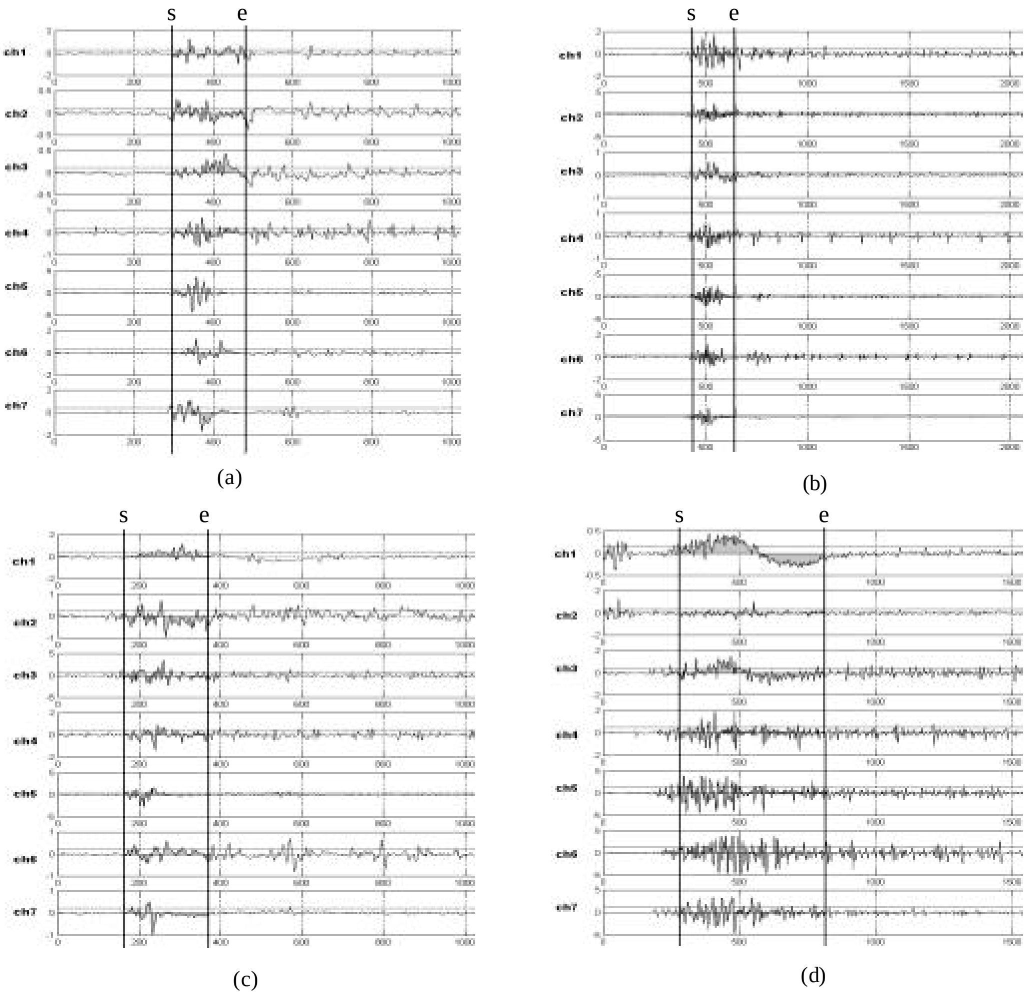

Figure 4. Typical results of multi-threshold method for (a) extension of the index finger, (b) extension of all fingers except the thumb, (c) extension of all five fingers and (d) supination. In the figure, s and e represent start and ending times of each action period, respectively.

Table 1. Discrimination rate using six features from seven electrodes. Where (1)-(11) represent hand action flexion down, extension of thumb and little fingers, extension of index and middle fingers, extension of all five fingers, extension of thumb and index fingers, extension of the index finger, extension of all fingers except the thumb, pronation, supination and flexion up, respectively.

1	2	3	4	5	6	7	8	9	10	11	average
90%	92%	89%	85%	94%	97%	92%	99%	97%	90%	99%	93.1%

Table 2. Discrimination rates using only one feature from each channel. Where (1)-(11) represent hand action flexion down, extension of thumb and little fingers, extension of index and middle fingers, extension of all five fingers, extension of thumb and index fingers, extension of the index finger, extension of all fingers except the thumb, pronation, supination and flexion up, respectively.

	1	2	3	4	5	6	7	8	9	10	11	average
IEMG	84%	87%	75%	82%	82%	93%	91%	84%	95%	76%	80%	84.5%
WAMP	49%	82%	75%	78%	67%	91%	84%	78%	69%	67%	80%	74.5%
SSC	67%	91%	71%	78%	75%	85%	93%	87%	84%	80%	91%	82.0%
VAR	76%	85%	69%	80%	82%	96%	93%	91%	78%	65%	87%	82.0%
WL	82%	98%	89%	85%	91%	98%	96%	82%	91%	82%	100%	90.4%
ZC	58%	71%	65%	71%	64%	85%	98%	67%	78%	64%	84%	73.2%

Table 3. Discrimination rates using (a) IEMG and WL, (b) ZC and WAMP. Where (1)-(11) represent hand action flexion down, extension of thumb and little fingers, extension of index and middle fingers, extension of all five fingers, extension of thumb and index fingers, extension of the index finger, extension of all fingers except the thumb, pronation, supination and flexion up, respectively.

	1	2	3	4	5	6	7	8	9	10	11	average
a	78%	98%	89%	89%	91%	98%	100%	98%	95%	75%	82%	90.3%
b	84%	96%	84%	82%	80%	95%	95%	80%	87%	78%	95%	86.9%

recognition period, EMG signals from each channel are normalized and continuously compared with corresponding thresholds. When two or more EMG signals exceed their corresponding thresholds, it is recognized as the beginning of one action. After the beginning of an action, when six or more EMG signals are determined to be below the corresponding threshold, it is marked as the end of action (Figure 1).

Six features from seven EMG signals each are used to classify 11 hand actions. Thus, an ANN with 42 input nodes and 11 output nodes is instituted for this study. A 28-node hidden layer is added to tighten the connection between the input and output layers. However, the amount of computation for this ANN may be too large for real-time discrimination in the future. Thus, experiments have been designed to examine the feasibility of reducing the number of nodes in the ANN.

Subject and Experiment

Eleven normal subjects were recruited for this study, including eight males and three females, with an average age of 24±3 years. The ring electrode system was placed on their forearm five centimeters below the elbow. Experiments were conducted while subjects were standing. During the training period, each subject was asked to do two hand actions, hand opening and closing, repeatedly. The EMG signals acquired during this period were used to establish thresholds and normalization factors for each channel. After the initial training period, subjects were asked to carry out the 11 hand actions 18 times in random order. All EMG signals were digitized using 2000Hz sampling rate and processed off-line using MatLab program. Three experiments are used to test the ability of the proposed system. First, all 42 features are used in the discrimination test. Second, only one feature from each channel is used. Third, two features from each channels are selected and input into the identify system.

Results

The active electrode, its frequency response and the ring electrode system are illustrated in Figure 2. It is clear that the active electrode does meet its original design specification. On the other hand, different EMG patterns during different hand motions can be clearly identified in the EMG signals that were acquired using the ring electrode system (Figure 3).

By using the proposed multi-threshold method, action periods can be reliably sectioned out. Although the detected starting and ending times may not be precise, the proposed method does the segmentation without error and uses minimum computation (Figure 4). After each action period is determined, six features from each EMG signal were calculated. Half of the hand actions were used as training data and the other half were used as test data. In the first experiment, six features from seven electrodes were input into the ANN, yielding an average discrimination rate of 93.1% (Table 1).

When only one feature from each channel was used, the discrimination rates ranged from 73.2% to 90.4% (Table 2). On the other hand, when two features with the highest discrimination rate in the previous results were selected, the average discriminative rate increased to 86.9% and 90.3% (Table 3). Additionally, the size of ANN is reduced to 14 inputs, 16 hidden and 11 output nodes.

Discussions and Conclusions

It is demonstrated that the custom-made active electrode provides clean EMG signals and the proposed ring electrode system offers a convenient way to acquire multiple EMG signals for hand actions. Although the determination of starting and ending times of each action period is not precise, the proposed multi-threshold method can identify all the action periods without error. Features extracted from each action period provide reliable information for discriminating different hand actions, which can be proved by the high average discrimination rate for hand and finger actions. However, for some finger actions, the discrimination rates are lower than the other actions. This may be because the ring electrode system was placed too far away from the muscle groups responsible for these finger actions. Nevertheless, with the aid of this ring electrode system, the six EMG features may be properly reduced to only two and still provide a satisfactory discrimination rate. Additionally, the size of the ANN can be reduced dramatically from 42*28*11 to 14*16*11 and the amount of computation is significantly reduced.

To explore other possible situations, two pilot studies were conducted. When the trained ANN weights of the same subject were used for trials on the following day, the discrimination rate dropped to 72%. During these two trials, the ring electrode system was carefully placed in the same position to avoid the effect of different electrode placement. This indicates that, in addition to the electrode placement, other factors such as the condition of the skin, the speed and force of the action can affect the accuracy of discrimination. On the other hand, when the trained weights from one subject were used by two other subjects, the discrimination rates were as low as 14% and 42.9%. This indicates that the between-subject variations are large enough and cannot be ignored.

On the other hand, to further increase the discrimination rates for finger actions, additional electrodes may be needed near the wrist. Moreover, the current system cannot detect movements of the upper arm. To identify motions involving the upper arm, one or more electrodes placed on the upper arm can help to discriminate the motions of upper arm. Nevertheless, the results indicate that, with the ring electrode system and signal processing methods, the proposed system does provide high discriminative ability for the actions of fingers, palm, wrist, and forearm. With additional electrodes and digital signal processor, this system can be further developed into a real-time hand action identification system for computer and prosthetic device control.

Acknowledgement

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