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An EMG-based Handwriting Recognition through Dynamic Time Warping

Gan Huang, Dingguo Zhang, Xidian Zheng, Xiangyang Zhu
State Key Laboratory of Mechanical System and Vibration
Shanghai Jiao Tong University
Shanghai, China, 200240
Email: huanggan1982@gmail.com

***Abstract*—In this paper, an electromyography (EMG)-based handwriting recognition method was proposed for a latent tendency of natural user interface. The subjects wrote the characters at a normal speed, and six channels of EMG signals were recorded from forearm muscles. The dynamic time warping (DTW) algorithm was used to eliminate the time axis variance during writing. The process for template making and matching was illustrated diagrammatically. The results showed that no more than ten training trials per character could make an accuracy of above 90%. The recognition performance was compared in three character sets: digits, Chinese characters and capital letters.**

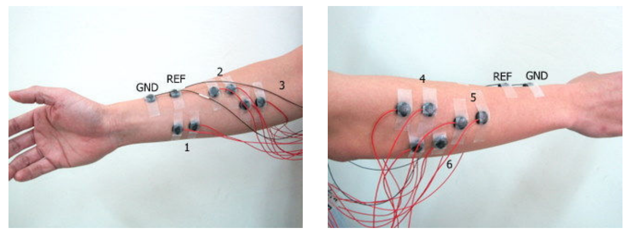

Fig. 1. The positions of six pairs of EMG sensors, and the ground and reference electrodes.

I. INTRODUCTION

Electromyography (EMG) signals are used in many clinical and biomedical applications, such as muscular disease diagnoses [3] and prosthetic control [2]. Researchers have also used EMG signals to control computers [13] and other devices, like robot and wheelchair [1]. Among the various applications, it is an interesting and promising research topic to recognize handwriting via EMG signals. However, it has no significant progress due to the technical limitations.

In Ref. [9], Linderman et al. conducted the study on handwriting recognition using EMG signals. In his experiment, the subjects were asked to write the characters from '0' to '9' (50 repetitions per character). The duration of each trial was 7s with 2-3s of which corresponding to character writing. Eight-channel EMG signals from hand and forearm muscles were recorded. As a result, recognition accuracy was 63% for five training trials per character. If the trials increased to 35 per character, the accuracy improved to 97%.

In this study, a fast handwriting recognition method based on EMG was proposed. In the experiment, subjects wrote the characters at a normal speed. The average time for writing a character was less than 1s, and fewer trials were used for training, which is more convenient for users.

This paper was organized as follows: Section II showed the experimental setup. Section III explained the method for data processing. The results and discussion were given in Section IV. Section V was the conclusion.

II. EXPERIMENT

A. Equipment and Setup

The forearm EMG signals were recorded using SynAmps system (Neuroscan, USA) with six pairs of sensors, and the sampling frequency is 1000 Hz with the cut-off frequency of 0.05-200 Hz. The subjects were asked to clean their forearms with scrub solution while we prepared the sensors with conductive gel and adhesive tape. In order to get the best possible signals, EMG sensing is traditionally conducted with two sensors spreading an inch apart on a muscle belly [12]. The positions of these electrodes are shown in Fig. 1. Six muscles were involved as follows: flexor carpi ulnaris, flexor digitorum superficial and palmaris longus, extensor carpi radials, extensor digitorum, extensor carpi ulnaris. The experimental setup took about 20 minutes.

B. Design and Procedure

During the experiment, the subjects wrote the characters, while their elbows were fixed and only their hands and wrists moved. They wrote the characters with a normal speed and strength as usual.

The experiment was divided into four phases.

1) calibration phase: The subjects wrote every character twice. This phase aims to help the subjects fit in with the surrounding. The system would set baseline in writing activity detection by these data.

2) training phase: In training phase, the subjects wrote each character several times. The obtained data were used to make templates.

3) testing phase: In this phase, the subjects also wrote each character several times. By template matching, the system recognized which character the subject wrote and displayed the result on the screen immediately. The recognition rate was given to evaluate the efficiency of the system.

4) playing phase: Some subjects may feel interested in the new writing style. The playing phase was set for subjects to

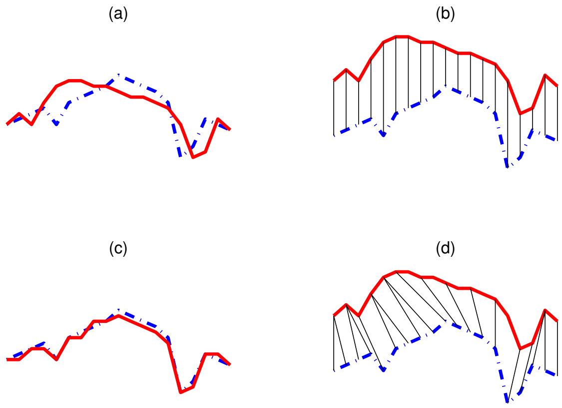

Fig. 2. An example for DTW algorithm. (a) The two time series are dissimilar in Euclidean distance. (b) They have the same overall waveforms but they are not aligned well in the time axis. (c) A more sophisticated distance measure is calculated after DTW algorithm. (d) The DTW algorithm provides a nonlinear alignment in the two time series.

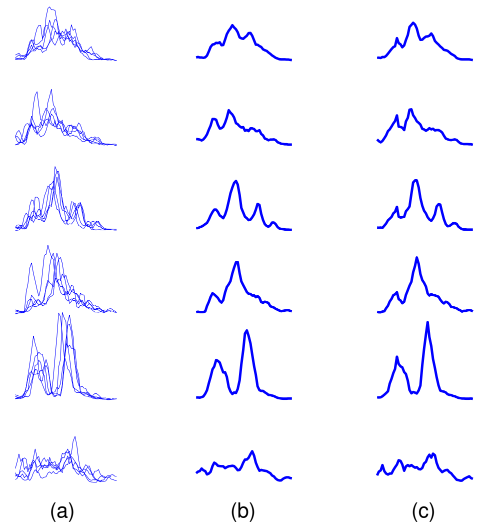

Fig. 3. Template making. (a) Five samples for writing character '2'. (b) The initial template. (c) The final template generated by iteration.

experience this novel input way and test its general recognition efficiency. The subjects could write freely as they wanted.

The experiment took about 1.5 hours.

III. Data Processing

A. Basic Signal Processing

The raw EMG signals are firstly bandpass filtered between 10 and 200 Hz. The notch filter at 50 Hz is enabled. Then muscle activation interval is determined when the sum of squares of the EMG signals crosses the baseline of 300 ms. The baseline is set to be 0.2 mean values of the sum of squares of the EMG signals in the calibration phase. For feature extraction, the absolute value of the segmented signals is smoothed with the 50 ms wide windows, and down-sampled to 66 Hz. A time series feature of six channels is generated.

B. Dynamic Time Warping

To compute the similarity between time series, Euclidean distance or some extension may be typically used. However, a small distortion in the time axis could make Euclidean distance much brittle. Hence, dynamic time warping (DTW) algorithm is introduced to align them in the time axis. Fig.2 provides an example to illustrate the condition. Two time series, which have approximately the same overall waveforms, are not close to each other in Euclidean distance. DTW algorithm can warp one time series nonlinearity to calculate the distance with the other time series more intelligently.

By means of dynamic programming, DTW algorithm can find an optimal alignment between two time series. This so-called trajectory-matching technique, originally designed by Kruskal and Liberman [8] for speech recognition purposes, is used successfully in gesture recognition [5], robotics [11], speech processing [10], manufacturing [6] and medicine [4]. A detailed explanation of DTW algorithm can be found in Ref. [7].

When the users write the same characters, they can't keep their rhythm constant. Some kind of distortion is unavoidable. Hence, DTW method can be used to eliminate the distortion and improve the correct recognition rate.

C. Template Making and Matching

For each character, the length of the template is determined by the average length of training trials, and the final template is achieved by iteration. The initial template is the average of the trials, where the trials are extend or stretch linearly to the length of the template. Then DTW algorithm is applied on every trials to find the corresponding time points in the template. The new template is made by averaging these time points. Empirically, one iteration is enough for template making. More iterations couldn't help improving the correct rate, but increase the computing complexity.

Fig.3 illustrates the operation of template making. Five samples have an overall similar waveform for writing character '2', but small variations exist in both rhythm and strength as shown in Fig.3(a). The initial template is made by the average of these samples. Using DTW algorithm, the template generated is sharper in Fig.3(c). Comparatively, the initial template in Fig.3(b) is smoother and some details in waveform are neglected.

For template matching, the distances between such a six-dimensional time series and the templates of each characters are calculated after nonlinear time warping. The character is determined by the template with the smallest distance.

An example of character recognition is shown in Fig.4. The forearm EMG signals for the subject writing the character '0' are plotted in the left. The time sequences of six channels correspond to the six forearm muscles. The segment, which is detected for writing, is highlighted by blue bar. It is smoothed and down-sampled for feature extraction, which is shown in red in the middle. Compared with the ten templates after

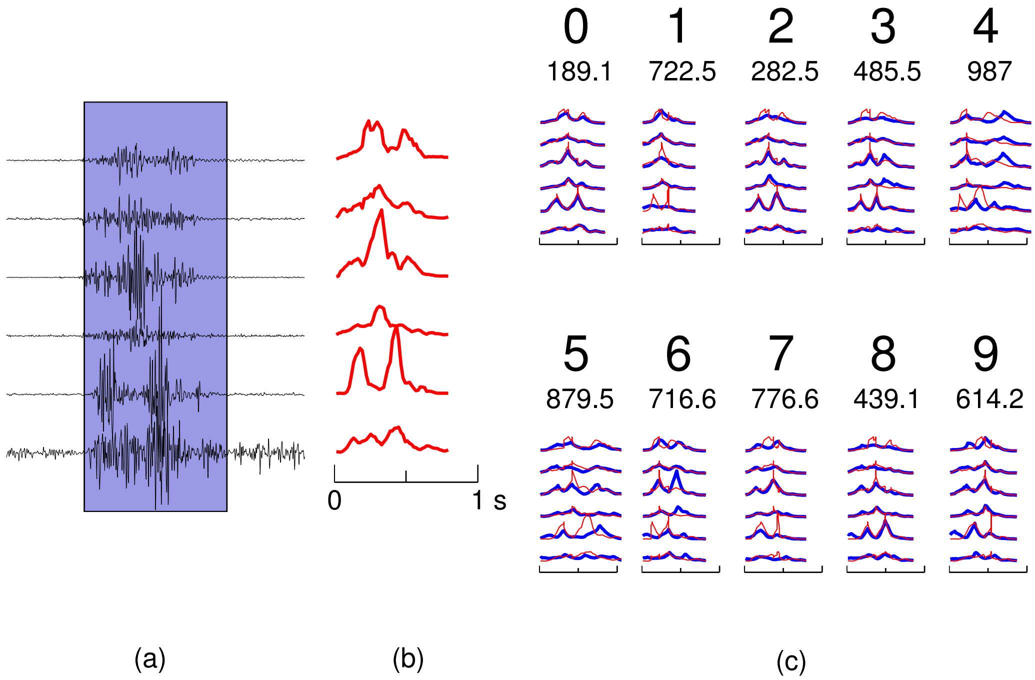

Fig. 4. An example for character recognition. (a) After band-pass filtering, the signal for the subject writing character '0' is segmented with blue bar. (b) Feature extraction is done by smoothing and down-sampling. (c) Compared with all the templates, the system recognizes the character corresponding to the smallest distance.

dynamic time warping, the character is determined by the template with the smallest distance. The comparison is given in detail in the right. The template for character '0'-'9' is plotted in bold blue line. It could be seen that the average time for the subject to write these characters is not the same. The subject writes '1' with about 0.7 second, but writes '4' and '5' much slower. Using DTW algorithm, the 0.8 second time series feature is warped nonlinearly into the length of the template, plotted in thin red line. The distance between the template and the feature is labeled above the template. The smallest distance 189.1 with respect to the character '0' determines what the subject writes.

IV. Results and Discussion

Three individuals volunteered to participate in the experiment, ranged from 25 to 28 years of age. All the subjects are right-handed, and no pathological muscular conditions or skin allergies are reported. The three subjects took the experiments two to four times. Eight datasets were collected for the character set '0' to '9', and each dataset contained $60-100$ repetitions per character. One of them took part in the experiment on other two character sets, the Chinese characters from one to ten and the capital letters from 'A' to 'Z' with sixty repetitions per character.

As shown in Fig.5, the accuracy increases along with the size of the training set. The accuracy grows rapidly as the size increasing from 1 to 5. Even if only one trial per character is conducted for training, an accuracy of about 70% could be obtained. The accuracy is improved to 93% as the training size increases to 20 per character. Compared with the 63% for 5 trials per character in Ref. [9], our method can use small sample size to get a higher accuracy, which is convenient for users.

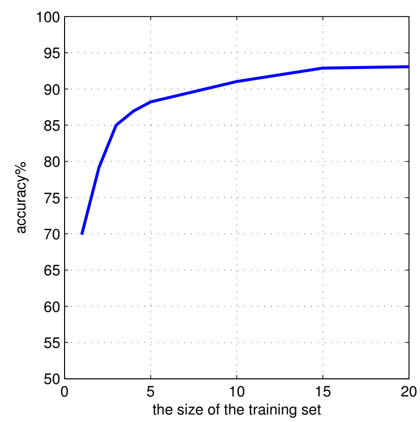

Fig. 5. The accuracy increases along with the size of the training set.

The performance of three different character sets is shown in Table I. These characters are listed in Fig.6. The accuracies on digits and Chinese characters have the higher accuracy than letters. It is mainly because of the large character set of letters.

In fact, the three sets have their own characteristics. For digits, most of them can be simply written by one stroke, except for '4' and '5' with two strokes. It is easy for segmenting in this case. However, considering the font style, digits

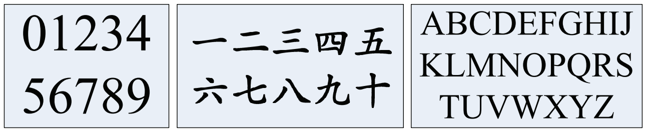

Fig. 6. Three character sets: digit characters from '0' to '9' , the Chinese characters from '一'('one') to '十'('ten'), and the capital letters from 'A' to 'Z'.

would be written more "softly" than Chinese characters and capital letters, which is unfavorable for recognition. Chinese characters have a totally contrary condition, and each of them consists of several strokes from one to five correspondingly, which is unfavorable for segmenting. For example, it is apt to wrongly segment the character '二'('two') or '三'('three') into two or three separate characters '一'('one'). The "harder" writing way can guarantee the accuracy after the proper segmenting. Capital letters have the merits of both digits and Chinese characters: no more than three strokes per character and writing in a "hard" way. However, they have some other problems. Although 'D' and 'P' have different character forms, they are written in a similar way, and the system is scarcely able to recognize one from the other. Other characters like 'A' and 'H', or 'B' and 'K' are also confused on some subjects. Writing these characters deliberately in an altering way can solve these problems effectively.

TABLE I
ACCURACY ON THREE CHARACTER SETS.

No.	character set	size	accuracy(%)
1	digits	10	98.25
2	Chinese	10	97.89
3	letters	26	84.29

V. CONCLUSION AND FUTURE WORK

A novel handwriting recognition method based on the forearm EMG signals has proposed in this paper. Using the DTW algorithm, the distortions in the time axis was eliminated. An accuracy of greater than 90% was achieved with no more than ten training trials per character, and it also demonstrated the effectiveness with small sample size.

The biggest challenge for handwriting recognition using EMG is the activity onset detection. It is hard for system to set a time interval (300ms in our method) to determine whether the subject writes several characters with one stroke continuously or one character with several strokes intermittently. The typical example shows the confusion between two Chinese characters '一'('one') and one Chinese character '二'('two'), as discussed above. A corrected detection may improve the accuracy. In future, we will investigate this issue.

The technique mentioned in this work potentially can substitute for current computer input devices or touch screens for text transmission. It can bring significant change for conventional human-machine interface, and make great convenience for the normal persons. In addition, the disabled with hand deficiency will particularly benefit more. Actually, we have recruited some amputees for this project, and the EMG from residual muscles of forearm will further evaluate the method.

ACKNOWLEDGMENT

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