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Improvements on EMG-based Handwriting Recognition with DTW Algorithm*

Chengzhang Li[1], Zheren Ma[1], Lin Yao, Dingguo Zhang[2], Member, IEEE.

Abstract— **Previous works have shown that Dynamic Time Warping (DTW) algorithm is a proper method of feature extraction for electromyography (EMG)-based handwriting recognition. In this paper, several modifications are proposed to improve the classification process and enhance recognition accuracy. A two-phase template making approach has been introduced to generate templates with more salient features, and modified Mahalanobis Distance (mMD) approach is used to replace Euclidean Distance (ED) in order to minimize the interclass variance. To validate the effectiveness of such modifications, experiments were conducted, in which four subjects wrote lowercase letters at a normal speed and four-channel EMG signals from forearms were recorded. Results of off-line analysis show that the improvements increased the average recognition accuracy by 9.20%.**

Keywords—Electromyography (EMG), Handwriting Recognition, Dynamic Time Warping (DTW), Mahalanobis Distance (MD)

I. INTRODUCTION

Electromyography (EMG) has been successfully applied in many areas as a type of human-computer interface. EMG-based handwriting recognition is also proposed in [1]. Several modifications have been conducted in [2]. However, due to the complexity of handwriting process, current recognition accuracy is still limited.

DTW algorithm has been widely used in various areas, especially in speech recognition [3]. In [2], DTW is introduced to the EMG-based handwriting recognition system to eliminate the distortion of signals in the time axis. However, the algorithm suffers from several flaws. Firstly, the approach for template making results in the lack of salient features for each template and therefore reduces the recognition accuracy. Moreover, Euclidean Distance (ED) is used to measure the difference between time series, which falsely assumes that each EMG channel is independent and equally weighted.

This paper proposes several improvements to further raise the recognition accuracy. A modified two-phase template making approach is introduced in order to generate templates with more salient features. Furthermore, taking the relationship among EMG channels into consideration, we substitute ED with mMD. In addition, the distances between samples and templates are discovered to be log-normally distributed after conducting log-normality tests. According to probabilistic properties of distance distributions, the thresholds are set up to reject abnormal samples. Experiments were conducted to validate the effectiveness of the modifications proposed.

Section II explains the data processing. Section III represents the experiments and results. Section IV is the discussion and future work.

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[1] Chengzhang Li and Zheren Ma made the same contribution to this paper, so they are the first co-authors.

[2] Dingguo Zhang is the corresponding author. (phone: 86-021-34206072; fax: 86-021-34206072; email: dgzhang@sjtu.edu.cn)

II. DATA PROCESSING

A. Data Pre-processing

Extracting signal waveform feature is important for subsequent data analysis. In this paper, wavelet analysis and band-pass filter are chosen to reduce noise while mean filter is introduced to make the features more salient.

Then, a two-phase segmentation method is developed to segment EMG signals.

a) First phase: The channel with the least noise is chosen to segment signals with a baseline, which is five times the mean signal amplitude when muscles are relaxed. One segment of signals is considered to be valid only when the length of the signals is more than 0.2s. One segment of valid signals is considered to be ended only when the signal amplitude is under the baseline for 0.5s.

b) Second phase: After extending the segments symmetrically by 50% in the time axis, for each EMG channel, the new baseline is re-defined as one-fifth the mean signal amplitude of extended segments. The start points and end points are determined with new baselines as in first phase. The start point of one segment is the average of start points in four channels. The end points are determined with the same means.

B. Dynamic Time Warping

The DTW algorithm is able to match two time series of unequal length by finding the optimal alignment between them through Dynamic Programming [4]. In conventional DTW, the difference between a testing sample and the reference is measured by ED. This paper proposed another approach to quantify the difference, which is based on Mahalanobis Distances (MD) [5].

1) Euclidean Distance (ED): In Euclidean Distance, each dimension of feature vector is treated equally and the correlations among different dimensions are ignored. The distance

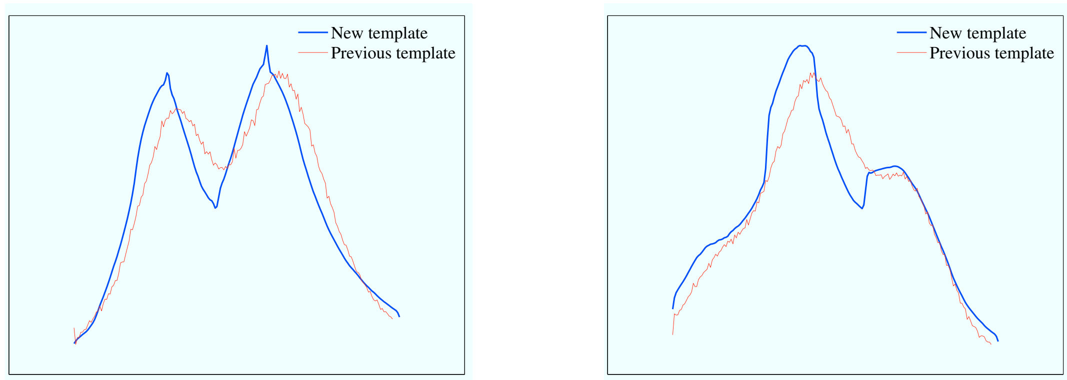


Fig. 1. Comparison between conventional and proposed template makings, which are with red lines and blue lines, respectively

equation is of the form,

$$ED(s_R, s_T) = \sqrt{\sum_{i=1}^{N} (R_i - T_i)^2} \tag{1}$$

where $ED(s_R, s_T)$ is the distance indicating the difference between two time series, s_R and s_T; R_i and T_i are the i^{th} sample points of time series, s_R and s_T.

2) modified Mahalanobis Distance (mMD): Mahalanobis Distance (MD) is proposed to measure the difference between time series, of which the form is,

$$MD(S_R, S_T) = \sqrt{(S_T - S_R)^T \Sigma^{-1} (S_T - S_R)} \tag{2}$$

where $MD(s_R, s_T)$ is indicating the difference between two time series, s_R and s_T. Σ denotes a full rank covariance matrix. Note Euclidean Distance can be seen as a special case of MD while taking identity matrix as covariance Σ .

In classical MD, Σ is estimated as the covariance matrix for the four-channel EMG,

$$\Sigma = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)(x_i - \mu)^T \tag{3}$$

where n is the sample size, x_i is the multidimensional vector, μ is a multidimensional vector consisting of the mean value of each dimension.

However, the conventional covariance matrix for Mahalanobis Distance merely considers the statistical characteristics of the whole data. To minimize the interclass variance, we employ a modified covariance matrix proposed by [6], of which the form is,

$$\Sigma = \frac{1}{|S_\omega|^{\frac{1}{d}}} S_\omega \tag{4}$$

where S_ω is defined as within variance matrix, of which the form is,

$$S_\omega = \sum_{t_1, t_2 \in T} \sum_{k} \left(t_{1(k)} - t_{2(k)}\right) \left(t_{1(k)} - t_{2(k)}\right)^T \tag{5}$$

where $T = \{t_1, t_2, t_3, \ldots, t_n\}$ is a set of genuine EMG signals for one letter. S_ω has a dimensionality $d \times d$. In this paper, we only employ the modified Mahalanobis Distance, of which covariance matrix is the within variance matrix S_ω.

It would be indicated that, for each letter or class, the distances between samples and final templates are log-normally distributed. The log-distance equation is used to modify measurement on difference between time series with ED and mMD, of which the form is,

$$\begin{cases} LED(S_R, S_T) = \log \sqrt{\sum_{i=1}^{N} (R_i - T_i)^2} \\ LmMD(S_R, S_T) = \log \sqrt{(S_T - S_R)^T \Sigma^{-1} (S_T - S_R)} \end{cases} \tag{6}$$

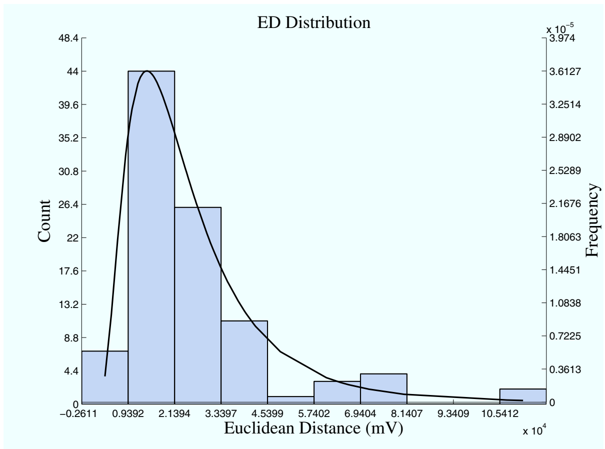
where $LED(S_R, S_T)$ is the log-Euclidean Distance, $LMD(S_R, S_T)$ is the log-modified Mahalanobis Distance. In template making and testing phase, all distances are calculated in log-distance.

3) Template making and distance distribution generation: To obtain the templates with more salient features, several modifications are proposed to improve the template making.

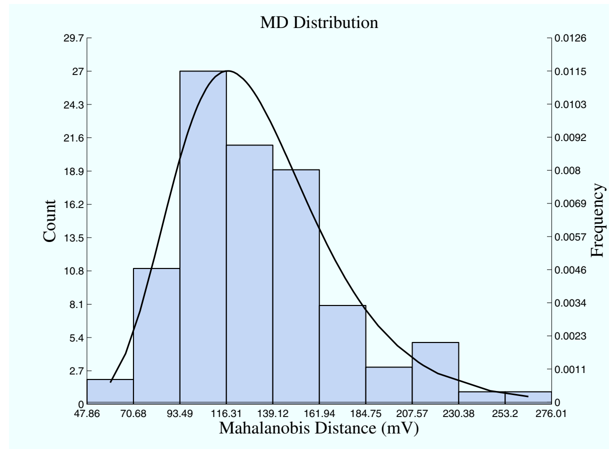
a) Two-phase template making: In the first phase, we carefully select the initial reference with the most salient features. Preliminarily, the five samples whose lengths are closest to the median length are selected as the candidate references. Subsequently, the distances between the five candidates and the rest samples are calculated. The one with the smallest sum of distances is chosen as the initial reference. Finally, samples of each letter are warped nonlinearly with the initial template through DTW algorithm. Then the initial template is generated by averaging those warped samples.

In the second phase, the initial template is used as the new reference to accomplish the time registration of all samples. Then the current template is generated as the average of the newly-warped samples. This current template would be acted as the reference for the next iteration. The difference between the current template and newly-generated template is measured by the average variance in the value of time points of templates. This phase is to be terminated on the condition that the average variance is less than 0.2%.

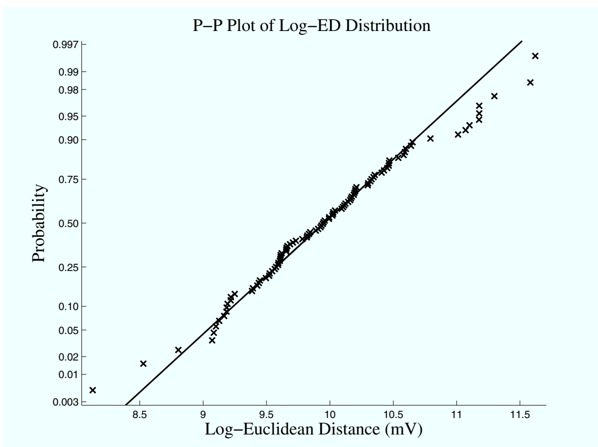
Figure 1 shows an example of template makings for two EMG channels of one letter with conventional and proposed approaches. According to the contour comparison, the new template generated by the proposed approach are with more significant "peaks" and "valleys" and thus are easier to be discriminated from one another.



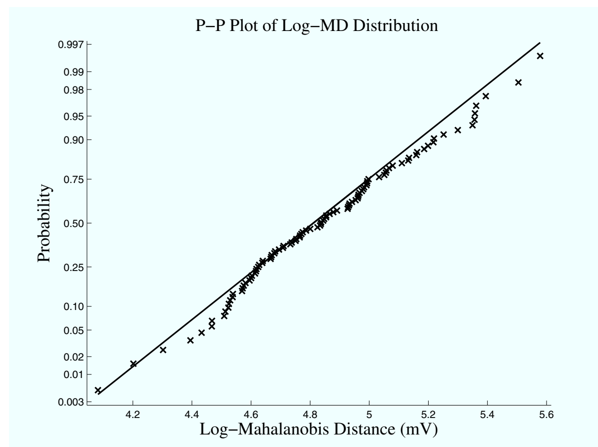
(a) ED Distribution



(b) mMD Distribution



(c) Log-Normality test on ED Distribution



(d) Log-Normality test on mMD Distribution

Fig. 2. Distance Distributions and Log-Nomality tests

b) Distribution generation: Taking “e” as an example, 100 four-channel EMG samples are collected. The distributions of distances between samples and their templates are generated with ED and mMD, respectively. After obtaining two distance distributions for “e”, both of the normality test and the log-normality test are conducted when choosing the significance level as 0.05. ED and mMD distribution and their corresponding p-p plots for log-normality tests are shown in Figure 2. The assumption that distances are normally distributed is rejected, and the one that the distances are log-normally distributed is accepted.

III. Experiments and Results

A. Experiments

The objective of the experiments is to evaluate the performance of the conventional DTW in [2] and the two novel methods proposed in this paper. One of the methods adopts modified template making approach, and the other adopts both modified template making approach and mMD. They are denoted respectively by DTW, DTW-T, DTW-Tm.

Four subjects participated in the experiments and they are referenced as Sub1-Sub4 in the following. Four EMG sensors were placed on the forearm of each subject with adhesive tape and the muscles involved are as follows: flexor digitorum superficial, palmarislongus, extensor carpi radials and extensor digitorum. A reference electrode was attached to the wrist of each subject to get clear EMG signals. The four-channel EMG signals were recorded with DataLOG (Biometrics Ltd.), sampled as 1000Hz with the cut-off frequency 50-200Hz. The experiment setup is shown in Figure 3.

During the experiment procedure, the subjects were first asked to relax for more than 10s to determine the baselines for EMG segmentation. The rest of the experiment consisted of 26 sessions corresponding with 26 lowercase letters, from “a” to “z”. Each session included 30 trials of writing one letter. There was a one-minute break after each session.

B. Testing

The 30 four-channel EMG samples were divided into five 6-sample groups. Five-fold cross validation was conducted and the results were averaged to obtain the final recognition accuracy.

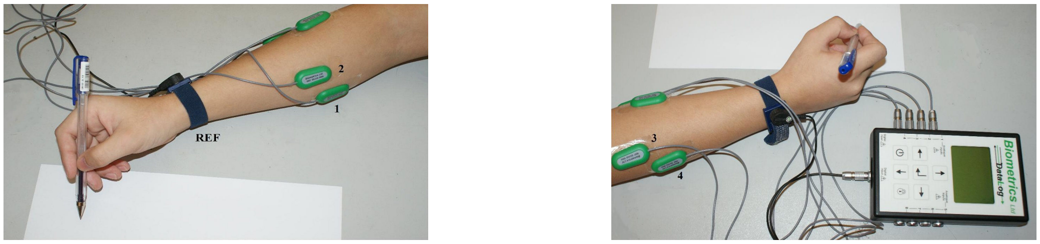


Fig. 3. Experiment Setup. Four-channel EMG data are collected.

1) Thresholds setup: After data processing, the threshold of the distance is set up, of the form,

$$C_i = M_i + 2\sigma_i \tag{7}$$

where C_i is the threshold for i^{th} lowercase letter, M_i is the mean value of distances between samples of i^{th} letter and the corresponding template. σ_i is the standard deviation of the distances between samples and the template of i^{th} lowercase letter.

2) Recognition Criteria: Each testing sample is matched to all 26 templates of lowercase letters. Two conditions have to be satisfied if sample i would be recognized as k^{th} letter. One condition is that the distance between sample i and the template of k^{th} lowercase letter, $D(S_i, T_k)$ is the smallest. The second is that the distance $D(S_i, T_k)$ is smaller than the threshold C_k. These two conditions are in the form as follows,

$$\begin{cases} D(S_i,T_k) = \min\{D(S_i,T_j)\} \quad j = 1,2,\ldots,25,26 \\ D(S_i,T_k) \le C_k \end{cases} \tag{8}$$

3) Results: Table I indicates the results of three recognition methods based on the data from four subjects. Compared with DTW, the modified template making approach enhances recognition accuracy by 4.65%. With both of the modified template making approach and mMD, the recognition accuracy was increased for a further step, by average 9.2% compared with DTW.

TABLE I
RECOGNITION ACCURACY FOR 26 LOWERCASE LETTERS ON 4 SUBJECTS

	DTW	DTW-T	DTW-Tm
Sub1	82.60%	86.64%	92.42%
Sub2	83.11%	87.23%	91.05%
Sub3	70.91%	74.93%	78.24%
Sub4	79.67%	86.10%	91.40%

IV. DISCUSSION AND FUTURE WORK

A. Effects of the modified training approach

With the modified template making approach, the average recognition accuracy is improved significantly by 4.65%. One key factor is that the new templates are made with more salient features. In [2], the linearly-stretching approach removes features from original data to a certain extent and only once iteration fails to produce a stable template. Therefore, the multi-iteration of template making approach is proposed to generate templates with more salient features. In addition, the initial reference is selected carefully to reduce convergence time for template making process.

B. Effects of mMD

With mMD in the recognition system, the average recognition accuracy was further enhanced by average 9.2% compared with DTW. When employed in speech recognition, DTW deals with one-channel signal, the utterance. Therefore ED is used to measure the difference between samples. However, in the field of EMG-based recognition, feature vectors are always multidimensional. The improvement results from the property of MD that considers the weighted channels and the within-variance matrix to modify the MD.

C. Future work

Although our recognition method is capable of conducting intelligent segmentation, further improvement is needed to segment EMG signals when writing intermittently. Additionally, unintentional outburst of movements should be removed from raw signals. Since the template making averagely requires two minutes for each letter, we should improve the efficiency of this system.

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