

Post-print of In-air Signature Authentication Based on Sequence Extremum Point Segmentation

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Date: 2018-05-20T00:00:00+00:00

Abstract

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Full Text

In-air Signature Authentication Based on Sequence Extreme Point Segmentation

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Abstract

In-air signature sequences are lengthy. To address the problems of slow matching and loss of local signature information caused by traditional global matching

methods, this paper proposes a method that segments signature data at extreme points before performing distance measurement. Furthermore, to tackle the mismatch problem of extreme points with different polarities that occurs in traditional DTW algorithms during extreme point matching, an improved DTW algorithm based on extreme point matching is proposed, which constrains the matching path rules of the DTW algorithm to avoid erroneous matching. On a local database, the system's False Rejection Rate (FRR) and False Acceptance Rate (FAR) reached 4.15% and 3.82%, respectively. Experimental results demonstrate that compared with traditional global matching algorithms, the method of first segmenting and then measuring similarity improves both the authentication accuracy and efficiency of the system.

Key Words: identity verification; accelerometer; extreme point matching; data segmentation; sequence alignment

0 Introduction

Identity authentication has permeated every aspect of people's work and daily life. Authentication methods can be mainly divided into two categories[1]: those based on what the user knows (such as passwords) and those based on what the user possesses (such as tokens). Although password authentication is widely used, passwords must be set with sufficient complexity to resist attacks, which simultaneously increases the difficulty for users to remember them. Traditional authentication methods based on physical tokens, while not requiring memorization, often suffer from authentication difficulties caused by users forgetting to carry or losing the devices. As traditional identity authentication methods gradually fail to meet users' requirements for information security, approaches that obtain users' biological or behavioral characteristics for identity authentication have attracted more attention. The comfort and security perception during authentication are two key factors for user acceptance of biometric authentication[2].

Commonly used biometric features include facial characteristics such as face[3], iris[4], and ear shape[5], as well as hand features including palmprint[6] and fingerprint[7] for identity verification. Behavioral characteristics such as gait[8], signature[9], and voice[10] have also been extensively studied in recent years. Nowadays, biometric authentication technology is attempting to employ methods that incorporate multiple features for user identity verification. In-air signature represents one such approach: two-dimensional signatures are already a widely used behavioral characteristic in biometric authentication, while differences in users' arm lengths, muscle strength, and wrist rotation angles also affect the signature acquisition process. Moreover, with the rapid development of sensor hardware technology, the collection of acceleration data for in-air signatures has become much more convenient[11]. Consequently, in-air signature authentication technology based on acceleration sensors is gradually becoming a popular research direction in the identity authentication field due to its characteristics of being easy to collect yet difficult to forge.

In recent years, research on identity authentication based on triaxial acceleration sensors has mostly focused on dynamic gesture authentication of simple characters, with the authentication process primarily employing global sequence-based dynamic programming algorithms. Reference[12] combined the Longest Common Subsequence (LCS) algorithm with Dynamic Time Warping (DTW) for gesture authentication on smartphones. Reference[13] analyzed the effectiveness of signature authentication by studying different scoring methods for the Global Sequence Alignment (GSA) algorithm. Reference[14] performed gesture matching and identity authentication using an improved DTW algorithm that constrained matching slopes. Reference[15] captured users' in-air signature trajectories through video and fused temporal and frequency domain information of signatures for identity authentication.

In daily life, users are more familiar with their own names and can develop specific writing habits. Chinese signatures are more complex and thus more secure and reliable compared to simple gestures. Although methods utilizing global features have achieved good authentication results, Chinese signatures generally take longer to write than gestures. Using global sequence alignment methods not only loses local signature information but also increases authentication time. The signature segmentation-based method proposed in this paper first matches extreme points of in-air signature sequences and then performs sequence segmentation after alignment, which not only reduces signature matching time but also utilizes the feature information of signature extreme points. The in-air signature authentication process is similar to two-dimensional signature authentication, consisting mainly of two stages: the training sample registration stage and the test sample authentication stage. The system authentication block diagram is shown in Figure 1 [Figure 1: see original paper].

1 Overall DTW Matching

1.1 Algorithm Principle

The in-air signature data collection process involves users holding a self-made circuit board containing an accelerometer and writing their signature in the air. The LSM303DLHC module on the circuit board adopts a micro-package that integrates a high-performance acceleration sensor to collect triaxial acceleration information of users' signatures (sampling frequency of 100 Hz). The triaxial acceleration data is transmitted via Bluetooth to a PC 端, where signature samples are stored in a database. Each signature sample consists of acceleration data from three axes, denoted as a_x, a_y, a_z , where the subscript is time-related, and the data collected at time is $a_{x,t}, a_{y,t}, a_{z,t}$, with acceleration units in m/s^2 .

Since the collected data includes a segment of static data at the beginning and end of the signature, the effective data is first truncated, and filtering is applied to remove noise interference from muscle tremors or the external environment. During the similarity measurement process between two in-air signatures, their triaxial acceleration sequences are matched separately using the DTW algorithm.

The overall DTW matching path for a user' s two signature x-axis acceleration sequences is shown in Figure 2 [Figure 2: see original paper].

DTW is a nonlinear time normalization technique that was early applied in speech recognition. Based on dynamic matching principles, it combines time and distance for normalization to minimize differences between two time sequences. Similar to speech, signatures exhibit variations in speed and force not only between different users writing the same signature but also between multiple writings by the same user. Therefore, the DTW algorithm can be applied in authentication research to measure differences between signature samples. The DTW algorithm implementation process assumes two time sequences R and T , corresponding to reference and test samples, where $R(m)$ and $T(n)$ represent the sampling points of the m -th and n -th frames, respectively, with consistent sampling frequencies between them.

The essence of dynamic programming is progressing from sub-stages to the overall stage. Sub-stages measure the similarity between R and T by calculating the distortion between any sample points. The distortion is expressed as shown in Equation (3). Based on the monotonicity and continuity constraints of the path defined in the algorithm, the next point from point (m,n) can only be $(m,m+1)$, $(m+1,n+1)$, or $(m+1,n)$. The distances between these three points and (m,n) are calculated separately, and the point with the minimum distance is selected as the next point to reach. Following these rules, the cumulative distance between two samples is calculated as shown in Equation (4).

After matching, the similarity of the triaxial acceleration between two signature samples is calculated separately. The similarity between the two signature samples is the average of the similarities of the three axes. During signature database establishment, three signatures from each user are taken as template signatures. The three templates are matched pairwise, and the template training distance result is the mean of the inter-template matching distances. The measured distance mean between the test signature and the three template signatures serves as the test distance result. The system threshold is Q , which compares the ratio of Q to the test distance and template training distance. If $\frac{Q}{\text{test distance}} < \frac{Q}{\text{template training distance}}$, the test signature is determined to be genuine; otherwise, it is rejected as a forgery.

Traditional DTW algorithms apply global sequence alignment to all signatures, which significantly reduces matching efficiency. To address this deficiency, this paper proposes a method of first segmenting signatures and then matching, transforming the global path planning problem into a local path planning problem.

2 Extreme Point Segmentation and Matching

2.1 Extreme Point Extraction

During the signature process, different users exhibit variations in stroke order, stroke length, and local speed and force, with each user developing specific writing habits. Key points of signature sequences include start points, inflection points, and extreme points[16-18], which are closely related to the signature process: the acceleration curve waveforms between each genuine signature of the same user show similarity and demonstrate stability in extreme point positions, while forgeries and genuine signatures exhibit certain differences in extreme point locations. Extracting stable extreme points from sequences is crucial for subsequent extreme point matching and segmentation. This section first explains the extraction of extreme points.

Considering that the collected acceleration sequence is discrete, extreme points cannot be obtained through differentiation. Therefore, the method compares a point with its neighboring points on both sides to determine whether it is an extreme point. For actual extreme points in in-air signature waveforms, to remove unstable extreme points caused by minor fluctuations during signing and reduce errors in subsequent extreme point matching, this paper extracts sequence extreme points following these rules:

- a) **Coarse extraction of extreme points:** If a is a point in the sequence, when its amplitude $a(k)$ is simultaneously greater than the amplitudes of 10 points on both sides, a is determined to be a maximum point; when it is simultaneously less than 10 points on both sides, it is determined to be a minimum point.
- b) **Alternating polarity:** If consecutive extreme points of the same polarity exist in the coarsely extracted sequence, the point with the maximum absolute amplitude is selected as the extreme point.
- c) **Polarity specification at ends:** The sequence starts with a maximum point and ends with a minimum point.

Following these rules, the extraction of sequence extreme points is completed, with the extraction process shown in Figure 3 [Figure 3: see original paper]. These extreme points are treated as a separate extreme point sequence. Since different signature sequences yield extreme point sequences of different lengths, to further align the extreme point sequences, the matching relationship between sequence extreme points must also be obtained.

2.2 Improved DTW Algorithm for Extreme Point Matching

This section discusses in detail the improved DTW algorithm that completes the extreme point matching process. Since the extracted extreme point sequence contains alternating maximum and minimum points, when aligning two sequences using traditional DTW, if the previously aligned extreme points have

the same polarity, movement in the diagonal direction on the path can achieve correct polarity matching. However, movement in horizontal and vertical directions causes erroneous matching between minimum and maximum points in the two extreme point sequences, as shown in Figure 4(a) [Figure 4: see original paper].

To address the problem of erroneous polarity matching of extreme points caused by horizontal and vertical movement, this paper modifies the transition rules of the D matrix in the DTW algorithm: the improved DTW algorithm changes the matching rules in horizontal and vertical directions to move two units at a time. This allows extreme points to skip points with different polarity on the matching path in horizontal and vertical directions and instead find the next point with the same polarity for matching. The transition rules for the D matrix of the improved DTW algorithm are shown in Figure 5 [Figure 5: see original paper].

Because the matching path rules of the improved DTW algorithm change, the transition rules of the redefined D matrix are as shown in Equation (8). Since the improved DTW algorithm skips the vertical direction point and horizontal direction point, the transition matrix adds a penalty distance in these two directions compared to the diagonal direction. The improved DTW algorithm effectively avoids erroneous matching between extreme points of different polarities in the two sequences, as shown in Figure 4(c) [Figure 4: see original paper].

Assuming two stable extreme point sequences are the template extreme point sequence R of length M and the test extreme point sequence T of length N . The signature acquisition captures triaxial acceleration signals, and the extreme points of the acceleration sequence projected on one axis contain four-dimensional data (x, y, z, t) , where x, y, z, t are the amplitudes of the extreme points in the $x, y,$ and z -axis directions. The redefined distortion between two sample points in the sub-stage template extreme point sequence and test extreme point sequence is shown in Equation (7).

2.3 Extreme Point Segmentation

The segmentation process divides two sequences into the same number of segments based on the obtained extreme point matching pairs. Since the extreme point matching pairs still contain cases where one extreme point matches multiple extreme points in another sequence, the segmentation process cannot be completed directly. When one-to-many matching of extreme points occurs, it is necessary to merge these multiple extreme points directly. The extreme point merging rule is defined as follows:

If in the aligned extreme point sequence, $R(m)$ matches multiple extreme points $(T(n), T(n+1), \dots, T(n+i), \dots)$, then during segmentation, the extreme points $(T(n), T(n+1), \dots, T(n+i), \dots)$ are merged, meaning only the match between $R(m)$ and $T(n+i)$ among the multiple matching pairs is used as the basis for

segmentation.

After obtaining the one-to-one correspondence between the two sequences' extreme points, sequence segmentation can be completed based on the extreme point correspondence information: the first segment is from the start points of both sequences to the first set of aligned extreme points, the last segment is from the last set of aligned extreme points to the end points of both sequences, and the middle segments are divided sequentially by each set of aligned extreme points. The extreme point matching process is shown in Figure 4 [Figure 4: see original paper].

After obtaining the one-to-one segment correspondence between the two sequences, each corresponding segment consists of non-equal-length sequences. This paper adopts the traditional DTW algorithm to measure inter-segment distances and uses the sum of all inter-segment distances as the final distance measurement result between the two sequences.

3 Experimental Results

3.1 Experimental Dataset

Currently, there is still a lack of research on in-air signatures both domestically and internationally, and consequently no public datasets related to in-air Chinese signatures exist. The dataset used in this paper's experiments consists of genuine in-air signature data from 36 users collected through the aforementioned method. During data collection, each user held a circuit board with an accelerometer and wrote their signature in the air. Other users recorded videos of the signature collection process and retained the users' two-dimensional signatures on paper. Forgers learned the users' signature content through the two-dimensional signature information and imitated the users' signature style by watching the signature videos. The forgeries in this dataset are active forgeries. Each user wrote their signature 20 times in the air, from which 3 sets of data were selected as the user's signature template library, and the other 17 sets were used as genuine samples for testing. Each user also required 20 sets of forged signature samples, completed by other users.

In summary, the dataset used in this paper's tests consists of 1,440 in-air Chinese signature samples, comprising 108 training samples, 612 genuine samples, and 720 forged samples.

During experiments, traditional DTW algorithms were used to match all test signature samples with template signature samples, and the number of mismatched samples among the 1,332 test samples was recorded under different system thresholds. Sample mismatch situations fall into two categories: forged samples incorrectly accepted and genuine samples incorrectly rejected. These are represented by the False Acceptance Rate (FAR) and False Rejection Rate (FRR), respectively. The Equal Error Rate (EER) is the value at which the system's FAR and FRR are equal. This paper uses FRR, FAR, and EER as

described above as system performance evaluation parameters.

3.2.2 Improved Segmented DTW Algorithm Matching

In experiments, the distance between test samples and template signatures after segmentation is the accumulation of inter-segment distances between the two sequences using the DTW algorithm. Inter-segment distances are also measured using the three distance metrics described in Section 1.2. According to the distance authentication criteria, the FRR and FAR results obtained from the three measurement methods are shown in Table 2 .

Table 2. Authentication Performance of Three Distance Metrics After Segmentation

Distance Metric	FRR (%)	FAR (%)
Manhattan Distance	4.15	3.82
Minimum Cumulative Distance D		
Euclidean Distance		

As shown in Tables 1 and 2, the segmented DTW algorithm proposed in this paper outperforms traditional DTW algorithms under different measurement methods. Both algorithms achieve the best authentication performance when using Manhattan distance as the measurement metric. The Detection Error Tradeoff (DET) curves for both algorithms under Manhattan distance are shown in Figure 7 [Figure 7: see original paper].

Figure 7 shows that compared with traditional DTW algorithms, the segmented DTW algorithm proposed in this paper reduces the system's FRR and FAR by 27.3% and 33.4%, respectively, improving authentication accuracy.

To further evaluate the authentication performance of the proposed algorithm, comparative experiments were conducted using traditional DTW algorithm, Longest Common Subsequence (LCS) algorithm, Global Sequence Alignment (GSA) algorithm used in reference[13], and the proposed method. The authentication results and average sample matching time for several algorithms under the same dataset and experimental environment are compared in Table 3 .

Table 3. Comparison of Authentication Performance Between Proposed Algorithm and Other Algorithms

Algorithm	FRR (%)	FAR (%)	Average Matching Time per Sample (s)
DTW			>10×
LCS			>10×
GSA			>10×
Proposed Method	4.15	3.82	

The comparison in Table 3 demonstrates that under DTW, LCS, GSA, and other global sequence-based dynamic programming algorithms, the system's FRR and FAR are all higher than those of the proposed method, and the system lacks real-time performance with slow sample matching rates. The single sample matching time is more than 10 times that of the proposed method. This indicates that the proposed scheme of segmenting first based on extreme points and then measuring inter-segment similarity utilizes local signature features, better distinguishes between genuine and forged samples, and transforms the global path planning problem into multiple local path planning problems, reducing computational complexity for sequence alignment and optimizing overall matching time.

4 Conclusion

This paper proposes a method of first segmenting using extreme points and then measuring distance for in-air Chinese signature authentication based on triaxial acceleration sensors. To address the mismatch problem of extreme points, an improved DTW algorithm is proposed to complete the alignment of extreme points and segmentation of sequences. Experimental results show that compared with direct overall sequence similarity measurement, performing similarity measurement after stable extreme point matching and acceleration data segmentation significantly reduces the system's FRR and FAR and greatly improves authentication efficiency.

The experiments in this paper were conducted on a self-built dataset. Future experiments can expand the dataset and increase age diversity among users for analysis. Different extreme point matching pairs have significant impact on sequence segmentation effects and experimental results, which can be investigated in subsequent research.

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