Score Level Fusion in DWT Domain On-Line Signature Verification

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Abstract

In multi-matcher verification system, scores from matchers are fused at a decision level. However, each matcher has generally a different optimum threshold from other ones and then it causes deterioration of total verification rate. In this paper, we take the multi-matcher DWT on-line signature verification system for example and introduce threshold equalization methods based on the complexity of a signature. Their effectiveness is confirmed in computer simulations.

1. Introduction

Nowadays, the person authentication method using biometrics attracts attentions. An on-line signature verification is one of such authentication methods. The signatures of users are captured as time-varying parameters such as pen-position, pen-pressure, pen-inclination and so on [1-4] using a pen-tablet system. Especially, it must be assumed that only pen-position parameter is available in the mobile terminal such as a personal digital assistant (PDA). However, there is vulnerability that the pen-position data are easily imitated since the signature shape is visible.

In order to cope with the above problem, until now, we have proposed to introduce the sub-band decomposition by the discrete Wavelet transform (DWT) into the on-line signature verification [5]. Moreover, we have proposed a multi-matcher DWT on-line signature verification system [6,7] to improve the verification performance. As a result, we noticed that fusing the best matchers did not always result in the best matching pair. One of the reasons is that the optimal threshold for each signature is different.

In this paper, we introduce threshold equalization methods into the decision making stage. Their effective-ness is confirmed based on experimental results using the multi-matcher DWT on-line signature verification system described in [6].

2. Multi-Matcher DWT On-Line Signature Verification System

The block diagram of the multi-matcher DWT on-line signature verification approach is shown in Fig. 1. The pen-position input consists of x and y coordinates. Moreover, we also use the pen-movement angle, the pen-movement acceleration, and the pen-movement vector parameters, all of which can be derived from the pen-position data [7]. These parameters are, respectively, as position, angle, acceleration, and vector for convenience. The time-varying signal of each parameter is decomposed into sub-band signals using the DWT. A verification score is obtained at each sub-band level for each parameter. At the decision stage, all verification scores are fused based on a weighted-sum rule to obtain the total score (TS). When the total score is larger than a threshold, the user is recognized as genuine. Please refer to [5-7] for more details.

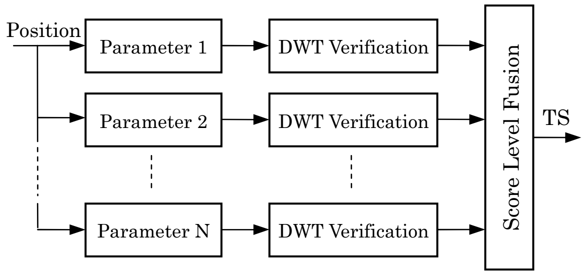
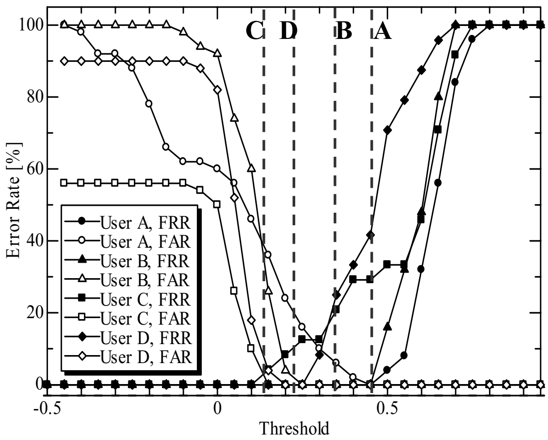


Figure 1. Multi-Matcher DWT On-Line Signature Verification system.

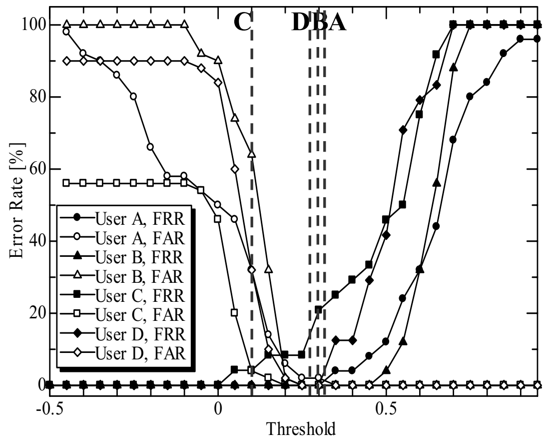
Based on this scheme, the multi-matcher DWT approach was evaluated in [7]. As a result, the best matched pair was obtained by combining the angle at s=2 and the acceleration at s=8, where s is a constant that defines the time shift in each parameter. On the other hand, the results also suggested that if the parameters which individually achieved the best performance were fused, it was not always guaranteed to obtain the best performance. In fact, the best performance (matcher) was individually obtained using the angle with s=4 and the acceleration with s=16.

One of the reasons is that the optimal threshold for each signature is different. Figure 2 shows examples of error rate curves of four users, where 2(a) shows the results of fusing individual best matchers, that is, the angle at s=4 and the acceleration at s=16 and 2(b) shows the results of the best matcher pair, that is, the angle at s=2 and the acceleration at s=16. In both figures, optimal thresholds for four users are illustrated as dashed lines (A, B, C, D). While it is easier to set an optimum threshold which is common to all users in 2(b), it is clear that such a common threshold achieves lower performance as shown in 2(a).

This result is related to the idea of writer-dependent threshold selection, which sets an optimal threshold depending on the writer (user) [2,8]. Furthermore, it is generalized as the user-specific matching threshold in [9].



(a)



(b)

Figure 2. Error rate curves of individual users in (a): individual best matchers and (b): the best matcher pair

The writer-dependent threshold values are found empirically based on error rates: Equal Error Rate (EER), False Acceptance Rate (FAR) and False Rejection Rate (FRR), which require the availability of forgeries. In general, biometric data of other users are used as impostor data. In the case of signatures, to use of other users' signatures as forgeries is called the random forgery scenario. However, as mentioned earlier the signature has the problem that it can be easily forged; therefore, it is reasonable to assume more severe or adverse conditions: simulated forgery in which genuine signatures are traced by forgers and/or the skilled forgery in which genuine writing styles are learned by forgers. However, it is difficult to collect such forgery data in practical applications since others must imitate genuine signatures whenever a new user is registered to a system.

In this paper, we propose to equalize optimal thresholds for users instead of using the writer-dependent threshold. This scheme does not require any forgery data.

3. Threshold Equalization

As a result of investigating the relationship between optimal thresholds and individual user signatures, we observed that the higher the complexity of a signature, the smaller the optimal threshold. This fact is explained as follows. In general, a complex signature requires long writing time, resulting in large variation in the signature of one individual (large intra-class variation). And even if the signature is genuine, such large variation makes the total match score smaller. On the other hand, when the signature shape is simple, the writing time is short and the signature is relatively stable. This makes the intra-class variation small and then the total match score becomes larger for genuine trials.

Thus, the different complexities of signature shape might cause different optimal thresholds for individual signatures. In the following sections, we propose three threshold equalization methods based on the complexity of a signature.

3.1 Method Based on Average Number of Sampled Data

A complex signature requires long writing-time, which increases the number of sampled data of the signature. Therefore, it is considered that the complexity of a signature is measured by counting the number of sampled data of the signature. The total score for each user is equalized by

$$TS^i_{eq} = k_R R^i_{tmp} TS^i \qquad (1)$$

where i is the signature index, R^i_{tmp} is averaged number of sampled data of genuine signatures (template) , TS^i is a total score at score level fusion, and TS^i_{eq} is a equalized threshold. In addition, k_R is a coefficient for setting the equalized threshold within the range from 0 to 1.

Small TS^i of a complex signature is multiplied by large R^i_{tmp} and then we obtained enlarged TS^i_{eq} . Oppositely, large TS^i is reduced by multiplying of small R^i_{tmp} . Thus, different optimum thresholds are equalized. We call this Averaging method.

3.2 Method Based on Number of Sampled Data with Negative Values

Next, we propose to examine the complexity of a signature based on the number of sampled data with minus values in the pen-movement angle parameter. Assuming the macro direction of pen-movement is from the left to the right, the negative value of the pen-movement angle means that a pen moves oppositely to the macro direction. If there are lost of negative values of the pen-movement angle parameter, it suggests the signature is a complicated one. Equalization is achieved by

$$TS^i_{eq} = k_\theta \theta^i_{neg} TS^i \qquad (2)$$

where θ^i_{neg} is the averaged number of sampled data with negative values in the pen-movement angle parameter in a template. k_θ is the coefficient for adjustment. We call this Negative method expediently.

3.3 Method Based on Number of Sampled Data with Sign Inversions

Finally, we propose to examine the complexity of a signature by using the number of sign inversions in the pen-movement angle parameter. The sign inversions in the pen-movement angle parameter correspond to the direction changes. In general, a complex signature has many direction changes. Thus, we define the equalizing method based on the sign inversions as

$$T\,S^{i}_{eq} = k_{sign} Sign^{i}_{alt}\, T\,S^{i} \quad (3)$$

where $Sign^{i}_{alt}$ is the number of sign inversions in the pen-movement angle parameter in a template. k_{sign} is the coefficient for adjustment. We call this Sign method.

3.4 Prevention of Excessive Equalization

If the averaged number of sampled data, sampled data with negative values, or sampled data with sign inversions of a signature is small, it means that the signature is not complicated. In such a case, the variation in the signature of one individual is small, so that the optimum threshold for each user is originally equivalent with those of others. Therefore, it needs no threshold equalization.

If the threshold equalization is applied to such equivalent thresholds, it inversely makes the thresholds unequalled. In order to cope with this problem, the proposed equalization is not achieved when the averaged number of sampled data, sampled data with negative value in the pen-movement angle parameter, or sampled data with sign inversions in the pen-movement angle parameter is smaller than 300, 300, or 150, respectively. These values were found out empirically.

4. Evaluations

In order to evaluate the performance of proposed three equalizing methods, we carried out simulations of the signature verification. 98 genuine signatures and 200 forgeries of 4 subjects were used. Conditions of the simulation are the same as in [5-7].

Tables 1-4 show the variations in EER by applying the three proposed threshold equalization methods in several fusion cases. In each column, the EERs with no equalization, by the Average method, by the Negative method and by the Sign method are presented from the left to the right.

Comparing with the EER with no equalization, the EERs of proposed three methods were almost decreased. In addition, to evaluate the effectiveness of the proposed methods quantitatively, we counted the number of fusion cases where the EER was decreased. In total 51 fusion cases, the Average method, Negative method, and Sign method decreased the EER in 43, 46, and 46 cases. They correspond to the improvement ratios of 84%, 90%, and 90%, respectively. From these results, it is clear that the proposed threshold equalization methods are effective for improving the verification performance in the multi-matcher DWT on-line signature verification system.

As an example of the results, equalized error rate curves of four users by using the Sign method are shown in the Figure 3. Compared with Figure 2(a), it is clear that the proposed threshold equalization is effective.

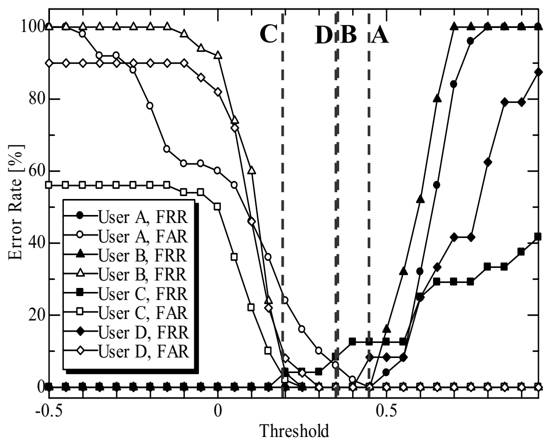


Figure 3. Error rate curves of individual users after having introduced the Sign method

However, we can also observe in some cases that the EER was deteriorated by introduction of threshold equalization methods. Especially, we confirmed a lot of deteriorations of the EER when combining the vector and the angle parameters (see Table 4). It needs further examinations. In addition, more work needs to be done in order to estimate the adjustment parameters, based either on experimental knowledge or statistical formulation.

Table 1. Variations of EER in fusing the pen-position and other parameters.

	Angle			
	s=2	s=4	s=8	s=16
Position	2.8→2.0→2.0→2.5	3.6→2.0→2.0→2.0	3.6→2.0→3.0→2.6	4.7→3.1→3.1→3.1

	Acceleration			
	s=2	s=4	s=8	s=16
Position	6.8→3.5→3.1→3.0	7.5→3.5→4.0→2.0	6.3→3.2→3.1→2.6	4.8→2.7→2.9→2.0

	Vector		
	s=4	s=8	s=16
Position	2.6→2.0→2.0→2.0	3.0→2.0→2.0→2.0	4.4→2.6→2.5→2.0

Table 2. Variations of EER in fusing the angle and the acceleration.

		Acceleration			
		s =2	*s* =4	*s* =8	*s* =16
Angle	*s* =2	5.3→3.1→3.6→3.1	5.0→5.1→4.0→3.6	2.0→2.0→1.5→1.0	2.0→2.2→2.0→2.0
	s =4	8.4→4.1→5.7→4.7	7.3→4.1→5.1→4.3	6.0→2.4→3.1→1.7	4.6→2.4→2.3→1.8
	s =8	8.8→4.6→5.6→4.4	8.4→5.1→5.7→4.2	6.2→3.1→4.5→2.8	3.5→2.5→2.3→2.0
	s =16	8.8→6.2→7.5→4.8	8.0→4.7→7.0→5.8	7.0→4.4→4.7→2.9	4.6→4.1→4.1→4.0

Table 3. Variations of EER in fusing the acceleration and the vector.

		Vector		
		s =4	*s* =8	*s* =16
Acceleration	*s* =2	6.3→4.6→4.9→4.0	6.6→4.1→5.1→4.0	9.7→5.7→6.0→5.9
	s =4	5.9→5.0→5.1→4.9	6.1→4.5→4.9→4.4	9.9→6.7→7.3→5.5
	s =8	5.0→3.1→3.7→2.5	5.0→3.0→2.8→2.3	7.5→5.1→5.1→4.1
	s =16	3.8→3.3→3.0→2.4	3.8→3.3→3.0→2.7	4.7→4.1→4.0→3.0

Table 4. Variations of EER in fusing the vector and the angle.

		Angle			
		s =2	*s* =4	*s* =8	*s* =16
Vector	*s* =4	4.6→6.3→5.5→5.4	3.0→4.1→3.5→3.9	4.0→3.8→3.2→3.1	4.0→4.1→4.1→4.0
	s =8	3.3→6.2→5.7→5.4	3.0→3.5→3.1→3.1	4.0→3.8→3.2→3.1	4.2→4.1→4.1→4.1
	s =16	4.1→5.6→3.8→4.6	4.0→3.6→3.1→2.7	4.9→4.9→4.1→3.4	5.3→5.2→5.1→5.1

5. Conclusion

In the multi-matcher system, there is a problem that the best performance is not always guaranteed even if the best matchers are fused. One of the reasons is that the optimal threshold for each user is different.

In this paper, we took the multi-matcher DWT on-line signature verification system for example and proposed threshold equalization methods based on the complexity of a signature. The results confirmed that the proposed threshold equalization methods were effective for improving the verification performance. On the other hand, there are remaining problems to be studied. The improvement of verification performance is not always guaranteed even when the proposed methods are applied. There may be also some other sources which cause different optimum thresholds.

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