A Robust On-line Signature Verification System

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Abstract

This paper proposes a robust on-line signature verification system based on a new segmentation method and fusion scheme. The proposed segmentation method resolves the problem of segment-to-segment comparison where the variation between reference signature and input signature causes the errors in the location and the number of segments. In addition, the fusion scheme is adopted, which discriminates genuineness by calculating each feature vector's fuzzy membership degree yielded from the proposed segmentation method. Experimental results show that the proposed signature verification system has lower False Reject Rate(FRR) for genuine signature and False Accept Rate(FAR) for forgery signature.

Key words : signature recognition, segmentation method, fusion model

1. Introduction

Signature has been used for a personal authentication method such as making a contract. Recently, researches on a signature recognition have been attracting attention as a biometic technique[1][2]. As for a signature recognition, however, contrary to other biometric methods, it has the problem that its skilled forgery is easy and system performance is often deteriorated by a signature variation by external and internal factors[3]. In order to solve this problem, researches on on-line scheme which uses both static and dynamic information are more in progress than off-line scheme which uses only static information.

The on-line signature verification method can be classified as point-to-point comparison and segment-to-segment comparison according to the comparison method between a reference signature and an input signature[4]. The segment-to-segment comparison method makes partitions by using either static information or dynamic information to find the optimum correspondence between segments after partitioning a reference signature and an input signature into each appropriate segment. In which, the static informations are such as vertex points and peaks[4][5][6][7], while the dynamic informations are such as the minimum velocity and pressure points[8], etc. The segment-to-segment comparison method like this has a disadvantage on which partition points even between genuine signatures can be unstable as it is difficult to partition all the signature into the same segment because of the signature variation, while it has an advantage that a regional comparison between segments is possible and analysis is easy since a statistic model can be regionally used.

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On the other hand, in the on-line signature verification, the data size is not consistent among genuine signatures as the input data is taken from a tablet or electronic pen. We generally apply an algorithm among HMM, neural network, and fuzzy logic[9][10][11] or perform resampling which often cause to loose principal features. Otherwise, one can match reference signature data and input ones by using DP(Dynamic Programming) algorithm[12].

To resolve the problems as above, we try to extract the stable partition points for the variational signatures without resampling. The proposed partition method makes stable partition by selecting peak points in one-dimensional Y axis. In addition, the final verification step is constructed to have superior performance by incorporating a fusion scheme which discriminates genuineness by calculating the fuzzy membership degree of each feature vector yielded by the proposed partition method.

The structure of this paper is as follows. Section 2 explains the proposed algorithm. Section 3 describes the results of the signature verification experiments. Finally we make conclusions in Section 4.

2. The new segment method and fusion model

The proposed signature verification system is shown in Figure 1. First, in the preprocessing, a signature data is obtained and normalized. The data through a tablet has static and dynamic informations such as X variation, Y variation, pressure, and time as shown in (1).

$$\text{Data} = \{x(i), y(i), p(i), t(i)\}, \quad i = 1, \ldots, n \qquad (1)$$

In the feature extraction process, the feature points of a signature are extracted by the proposed partition method. In the recognition part, similarity between an input signature and a reference signature is computed by using the fusion model and then a signature genuineness is discriminated by a threshold value.

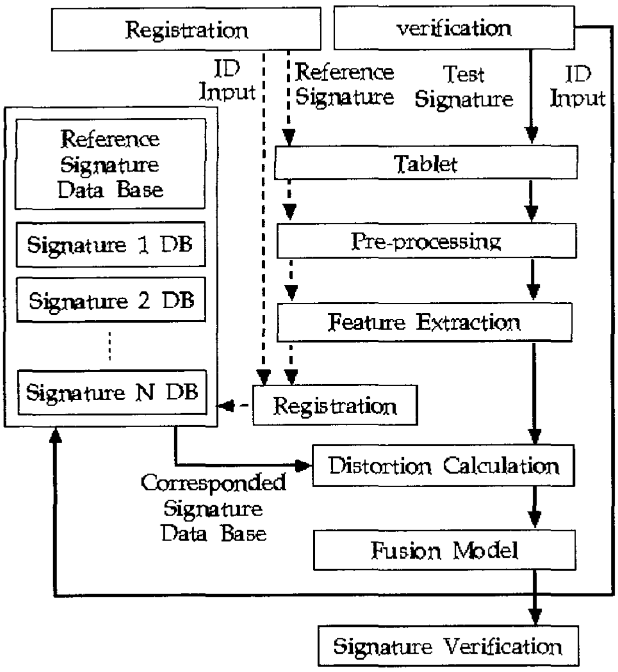
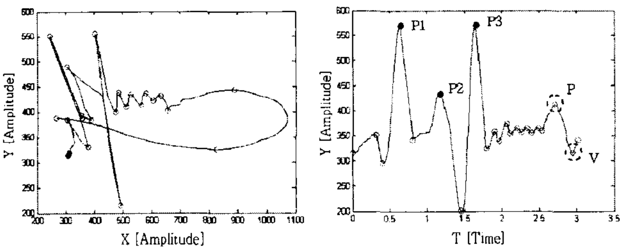


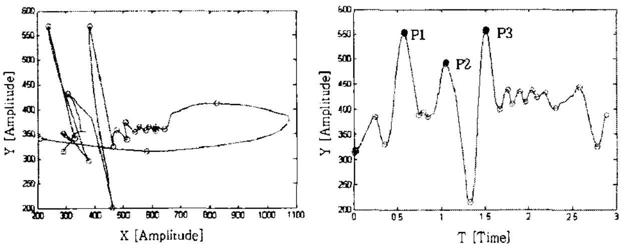
Fig. 1. The proposed on-line signature verification system

2.1 The feature extraction by a new partition method

In case of segment-to-segment comparison, the stable extraction of a feature vector, is highly relevant to system performance. For this, segment-to-segment comparison between reference and input signature is stably performed with peak and valley points of each section between two signatures are compared after the peaks of one-dimensional Y axis are selected. Fig. 2 shows an example of a standard partition selection.



(a) Signature 1

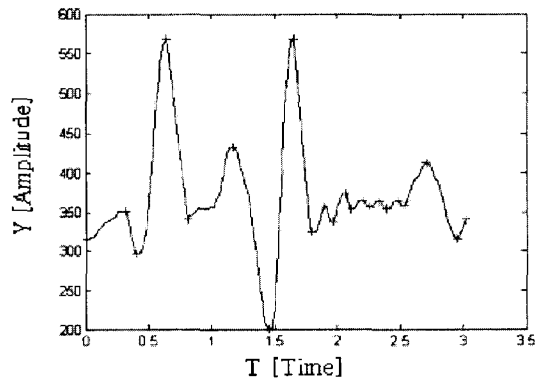


(b) Signature 2

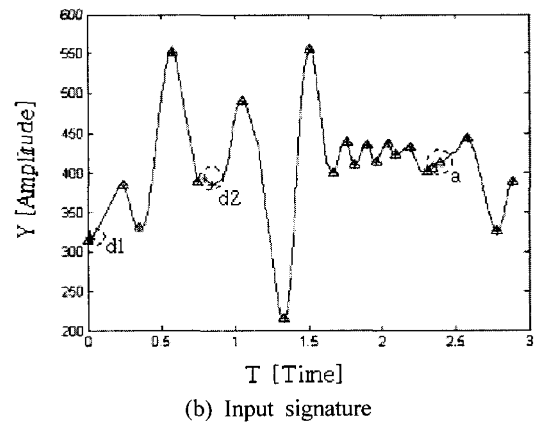
Fig. 2. The peak and valley variation in Y between genuine signatures

As shown in Fig. 2, there occurs an inconsistency of the peak (P) or the valley (Y) in Y axis between reference signatures and input signatures. The Fig 2, however, shows in which the peaks, P1, P2, P3, exist consistently regardless of the variations between the two signatures. These points are referred to as PPP(Partitioning Peak Points) in this paper. The PPP of a reference signature are usually consistent in most signature, in order and the three highest values are selected as PPP in this paper. The PPP of an input signature are selected by referring to the location of the sequence normalized based on the PPP of a reference signature.

After selecting the partition section of a comparison signature, perform the process of matching peak points and valley points of a reference signature and an input signature in each section. The matching is made by locating peak points and valley points of similar comparison signature with sequence location based on a reference signature after normalizing a reference signature. Under the condition that the sequence location, for the peak points and valley points of a reference signature, is compared with those of an input signature in each section, if the number of the two points is more than that of an input signature, the peak points or valley points of the input signature which has big difference in the sequence are deleted while ones which has small difference are added. In this case, it is highly possible that there is an error in addition/deletion of peak points and valley points if



(a) Reference signature



(b) Input signature

Fig. 4. matched peak and valley points between reference and input signature

the sequence information is only used in matching. In order to reduce this error, the peak points and the valley points are respectively separated and then we extract correspondent points between reference signature and input signature. Fig. 4 shows the result which detected the correspondent points between reference signature and input signature. Here, "+" means peak points and valley points before matching while "△" means ones after matching. In addition, "d1" and "d2" means where the unnecessary peak points and valley points are deleted while "a" means those are added.

2.2 A signature verification by a fusion model

The proposed fusion model is composed of the comparison part and the decision part which discriminate the genuineness of an input signature. In the comparison part, the error rate of each feature vector shown in Table 1 is computed by (2). The final decision step, as shown in Fig. 5, has the structure which discriminates genuineness by calculating the membership degree of each feature vector yielded by the proposed partition method and Z-Membership Function(ZMF). ZMF is the same as (3) where Thr^j_{high} and Thr^j_{low} are the critical value for the average error rate between a reference signature and an input signature the values obtained through the experiment. Since the proposed fusion model determines the membership degree of each feature point independently, the membership degrees for some features become lowered, it doesn't have a critical effect on the output value for the final verification. This renders superior performance than conventional method.

$$F_j = \sum_{i=0}^{N} \| F^j_{iR} - F^j_{iT} \| \qquad (2)$$

where

F^j_{iR} : jth feature value for ith matching point in a reference signature

F^j_{iT} : jth feature value for ith matching point in an input signature

N : the total number of matching points

F_j : an average error rate for jth feature, $j = 1, 2, ..., 5$

$$\begin{aligned}
D_j &= 1, && F_j \le Thr^j_{low} \\
D_j &= 1 - \frac{2(F_j - Thr^j_{low})}{(Thr^j_{low} - Thr^j_{high})^2}, && Thr^j_{low} < F_j \le \frac{(Thr^j_{low} + Thr^j_{high})}{2} \\
D_j &= \frac{2(Thr^j_{high} - F_j)}{(Thr^j_{low} - Thr^j_{high})^2}, && \frac{(Thr^j_{low} + Thr^j_{high})}{2} < F_j \le Thr^j_{high} \\
D_j &= 0, && F_j \le Thr^j_{high} \qquad (3)
\end{aligned}$$

Table 1. Feature vectors used in sign verification

No.	symbol	Meaning of Feature
1	Y_C	position in y-axis
2	Y_T	time in y-axis
3	Y_{DT}	duration between segments in y-axis
4	Y_V	velocity in y-axis
5	Y_P	pressure in y-axis

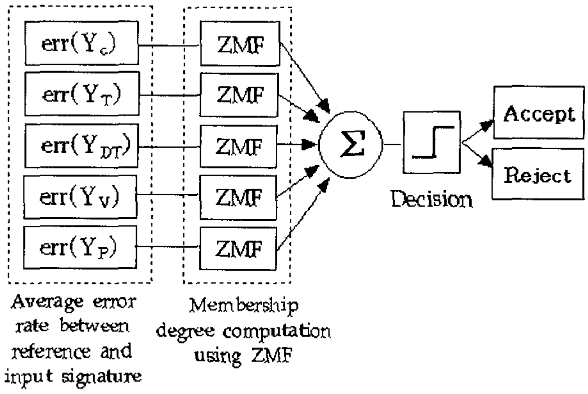


Fig. 5. Sign verification method used in fusion model

3. Experiment and Analysis

The tablet used in this paper is Intuos 4×5 from WACOM this takes about 100 points per second. We used total 300 of signature data containing 10 genuine signatures and 20 forgery signatures from 10 people. With regard to forgery signature, we collected them after sufficient training process through several times of repetition. In each person's signature, we used 2 of 10 genuine signatures as reference signatures and used the rest 8 genuine signatures, 20 forgery signatures, and 252 random forgery signatures as input signatures.

Table 2 show the recognition result for each feature vector. The most widely used DP(Dynamic Programming) method and the proposed segmentation method are compared. When FAR(False Accept Rate) is 0% for the forgery and random forgery signature, FRR for each feature vector of a genuine signature is improved form minimum 2.5% to maximum 36.25% comparing as shown in Table 2 except for Yc which may be a static information for a skilled forgery. We observe that the proposed method consistently finds the peak and valley points between a reference signature and an input signature. And also, dynamic information is more efficient than static one in discriminating a genuine signature from the forgery signature.

On the other hand, Table 3 shows the final verification rate by using fusion model , in which each FRR and FARs have improved 2.5% and 0.35%, 0.42%, respectively. Also we find that the results are better than the case of each feature vector shown in Table 2. Moreover, the discrimination of genuineness by the proposed fusion model makes the feature which has some large average error rate avoid having critical effect on the final verification. This renders robustness for signature variations since it is determined by all selected feature vectors' membership degree.

4. Conclusion

This paper proposed a robust signature verification method through the segmentation method and the fusion model. The proposed method can reduce errors by using PPP points between a reference signature and an input signature. We obtained high verification rate by means of the fusion model in the final variation step for the various on-line signature verification experiments.

Table 2. FRR for each feature vector

[unit: %]

Feature	The proposed method	DP method
	genuine	genuine
Y_C	47.5	40
Y_T	28.75	47.5
Y_{DT}	3.75	6.25
Y_V	10	46.25
Y_P	38.75	57.5

Table 3. The total verification rate

[unit: %]

	FRR		FAR			
	The proposed method	DP method	The proposed method		DP method	
	origin	origin	forgery	random	forgery	random
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	12.5	0	0	2	0
9	12.5	12.5	1.5	1.38	2.5	5.6
10	0	12.5	0	0	0.5	0
Total	1.25	3.75	0.15	0.14	0.5	0.56

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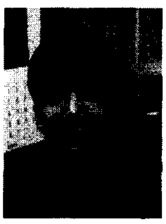

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