Offline signature verification with generated training samples

B. Fang, C.H. Leung, Y.Y. Tang, P.C.K. Kwok, K.W. Tse and Y.K. Wong

Abstract: It is often difficult to obtain sufficient signature samples to train up a signature verification system. An elastic matching method to generate additional samples is proposed to expand the limited training set so that a better estimate of the statistical variations can be obtained. The method differs from existing ones in that it is more suitable for the generation of signature samples. Besides this, a set of peripheral features, which is useful in describing both the internal and external structures of signatures, is employed to represent the signatures in the verification process. Results showed that the additional samples generated by the proposed method could reduce the error rate from 15.6% to 11.4%. It also outperformed another existing method which estimates the class covariance matrix through optimisation techniques. Results also demonstrated that the peripheral features are useful for signature verification.

1 Introduction

Offline signature verification is a formidable task [1–4]. One realistic problem is the lack of sufficient signature samples from each writer for training up the system. The difficulty is attributable to the private nature of signatures. Another reason is that handwritings vary with time. Hence, it is desirable to collect the signatures from a writer over a period of months instead of collecting all samples in one session. However, it is difficult to arrange numerous appointments with each writer.

With insufficient training samples, the estimation of the statistical parameters such as the mean feature vector and covariance matrix becomes unreliable. One solution is to apply some regularisation to the sample covariance matrix [5, 6]. In this paper, an alternative approach has been adopted. A method is proposed for generating a large number of additional training samples from the original small training set, and all these samples are used for estimating the covariance matrix. The method is incorporated into an offline signature verification system. A set of peripheral features is employed to represent the signatures. These features were originally used in character recognition and were found to be effective in representing the outline and internal structures of characters [7]. This work extends the application to offline signature verification.

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2 Elastic matching method for the generation of additional training samples

A method to tackle the problem of insufficient training samples is to generate additional training samples from the existing training set by applying distortions to existing training samples. It is hoped that the resulting estimated statistics will give a better performance. Leung *et al.* generated additional Chinese character samples by applying random shearing and local expansion and contraction to the original training samples [8], as shown in Fig. 1. Other examples can be found in [9, 10].

It is tempting to apply the same distortion technique as illustrated in Fig. 1 for generating additional signatures for improving the training. However, the problem is that there is no guideline on how much distortion should be applied. If the distortion is too much, the generated samples may lie outside the normal variations of the authentic signatures, and the system being trained up will have a greater chance of accepting forgeries as authentic signatures.

A conservative guideline on the amount of distortion is illustrated in Fig. 2. The overlaid images of two authentic signatures are shown in Fig. 2*a*. The corresponding strokes are identified and the displacements between them are indicated by displacement vectors in Fig. 2*b*. The proposed guideline is that the generated sample should lie within the space spanned by the displacement vectors, as shown in Fig. 2*c*. The rationale is that the generated signatures are then within the bounds of variations of the original authentic samples.

It is difficult to implement the proposed guideline for generating distorted signature samples with existing algorithms which apply distortions such as random shearing, expansion or contraction to the given authentic samples, without knowing the bounds of variations of individual strokes for the samples inside the training set. In this paper, an algorithm is proposed to generate distorted samples which satisfy the proposed guideline.

2.1 Two-dimensional elastic matching

Let a set of authentic signatures be available for training. Each time, two signatures are selected from this set. An

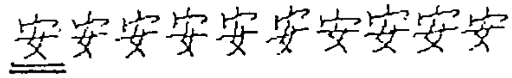

Fig. 1 *Generation of distorted characters from a given seed sample by applying random shearing, local expansion and contraction [8]*

The seed is underlined

Fig. 2 *Signature matching method*

a Pair of authentic signatures, shown overlapped
b The pair of authentic signatures with the corresponding strokes identified and linked up by displacement vectors
c Additional signature (dark grey) is generated by making use of the displacement vectors to 'interpolate' between the original pair of authentic signatures

elastic matching algorithm is then applied to this pair of signatures to establish correspondences between individual strokes, as shown in Fig. 2*a* and *b*. Corresponding stroke segments are linked up by displacement vectors in the Figure. An additional sample for training is then generated by utilising these displacement vectors to 'interpolate' between the pair of authentic signatures, as shown in Fig. 2*c*.

The proposed elastic matching algorithm was originally used for the recognition of handwritten Chinese characters [11, 12]. It is extended in this study to generate additional signature samples. Let the two signatures to be elastically matched be called A and B. An example is shown in Figs. 3*a* and 4*a*. Thinning is performed so that the resulting patterns consist of lines and curves only, as shown in Figs. 3*b* and 4*b*. These lines and curves are approximated by fitting a set of straight lines which are derived by using a minimum square error procedure [13]. Each resulting straight line is then divided up into smaller segments of approximately equal lengths, as shown in Figs. 3*c* and 4*c*. The number of segments in the two patterns may be different. Details of the matching method can be found in [11, 12]. A brief explanation is as follows.

The two skeletons approximated by straight segments are put on top of each other, as shown in Fig. 5*a*. The

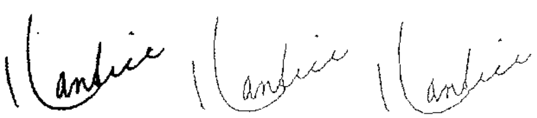

Fig. 3 *Signature A*

a Original image
b Skeleton
c Skeleton approximated by short straight line segments

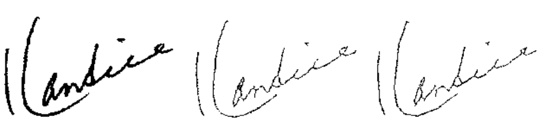

Fig. 4 *Signature B*

a Original image
b Skeleton
c Skeleton approximated by short straight line segments

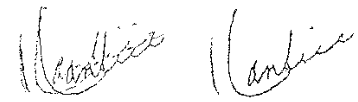

Fig. 5 *Elastic matching*

a Overlapped images of the approximated skeletons of signature A (black) in Fig. 3 and Signature B (grey) in Fig. 4 before matching
b Overlapped images after matching

segments in the skeletons are then gradually attracted towards each other in successive iterations so that the corresponding segments finally meet, as shown in Fig. 5*b*. An energy function is defined for each iteration so that optimal matching is achieved by minimising this function. The function consists of two terms: the first term measures the overall distance between the two patterns while the second term measures the deformation. Minimising this function tends to move the corresponding segments in the two patterns towards one another with minimum deformation. A neighbourhood of influence is defined for each iteration. Initially, a large neighbourhood is defined for each segment being moved, such that the individual movement tends to align the collective properties within the neighbourhood of the two patterns. The size of the neighbourhood is gradually decreased in successive iterations so that more and more local properties are used to direct the movement. The procedure thus works by first aligning global features (coarse match) and gradually aligning more and more local features (fine tuning).

2.2 Generation of additional signatures from pairs of matched signatures

At the end of the iterations, the corresponding strokes of the two signatures should hopefully be nearest to each other, as shown in Fig. 5*b*. A list of matches between each segment of signature A and the corresponding segment of signature B is drawn up. The displacement in position between the pair of corresponding segments in the two patterns is defined as the displacement vector. This is illustrated in Fig. 2*b*. By using the displacement vectors, an additional signature can be generated by 'interpolating' between the original pair of authentic signatures, as shown in Fig. 2*c*. A simple way to achieve this is by moving each pixel of signature A halfway along its displacement vector towards the corresponding stroke of signature B. However, the resulting pattern may not be locally smooth and continuous. To overcome this problem, a neighbourhood of correlation is defined for guiding the movements of the pixels of signature A. Instead of letting each pixel of the pattern move according to its own displacement vector only, the movement is made to correlate with that of adjacent pixels. The amount of movement for each pixel of the pattern is given by a weighted sum of the displacement vectors of the feature points in the correlation window.

Experiments show that the distorted signature generated by deforming signature A may still be not locally smooth and connected. Hence, the morphological operation of closing is applied to bridge gaps and fill holes in the distorted pattern. However, some details of the distorted pattern generated will vanish when using the closing operation. In order to satisfy this problem, a circular structural element with the smallest radius of one pixel has been adopted for the closing operation. An example of the generated pattern is shown in Fig. 2*c*. Further examples are given in Figs. 3 to 6.

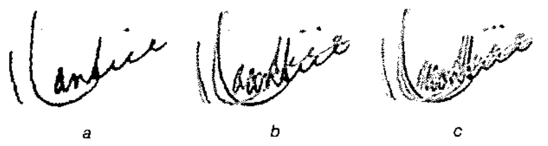

Fig. 6 *Further example of a generated pattern*

a The generated additional signature pattern from the original signatures in Figs. 3 and 4
b Overlapped images of the original signatures A (black) and B (grey)
c Overlapped images of the generated additional signature pattern (dark grey) and the original signatures A and B

3 Peripheral features for signature verification

A set of peripheral features, which is useful in describing both the internal and external structures of signatures, is employed to represent the signatures in the verification process [7].

3.1 Feature extraction method

The peripheral features ET1 and DT12 were originally proposed for character recognition [7]. The ET1 feature is defined as follows. The signature image is divided into a number of horizontal strips and vertical strips. Within each strip, the area between the edge of the virtual frame and the first white-to-black pixel jump is calculated. This operation generates a $4 \times N_p$ peripheral feature vector (4 edges with N_p strips for each edge). The ET1 feature is illustrated in Fig. 7. It can be observed that the ET1 feature is well suited for describing the outline (or external shape) of the signature pattern.

The second type of feature is the differential peripheral feature DT12. The signature image is divided into a number of horizontal and vertical strips. For the horizontal strips, the pixels are traversed row by row. The horizontal distance between the first black-to-white jump and the second white-to-black jump is obtained. Within each strip, the distances so obtained are summed up. Similar operations are carried out for the vertical strips (i.e. the pixels are traversed column by column). Hence, a $4 \times N_p$ peripheral feature vector is obtained (4 edges with N_p strips for each edge). The DT12 feature is illustrated in Fig. 8. It can be observed that the feature depends on the relative positions of the internal strokes of a signature. Hence, it reflects the internal structure of the pattern and should be useful for signature verification.

As the magnitudes of the ET1 and DT12 features depend on the image size, the features are normalised by dividing each feature value by the area of the image frame.

3.2 Training and verification protocol

Assume that the signature image is divided into N_p vertical strips and N_p horizontal strips for extracting the ET1 and DT12 peripheral features. The resulting feature vector then consists of $8 \times N_p$ components. Let the vector be denoted by $\boldsymbol{F} = (F_1, \ldots, F_{8 \times N_p})^T$ where ^{T} stands for transpose.

If there are N training signatures from a writer, the statistics of the peripheral features can be represented by the maximum likelihood estimates of the mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ of these vectors, where

$$\boldsymbol{\mu} = \frac{1}{N} \sum_{k=1}^{N} \boldsymbol{F}_k \tag{1}$$

$$\boldsymbol{\Sigma} = \frac{1}{N} \sum_{k=1}^{N} (\boldsymbol{F}_k - \boldsymbol{\mu})(\boldsymbol{F}_k - \boldsymbol{\mu})^T \tag{2}$$

where $k = 1, 2, \ldots, N$.

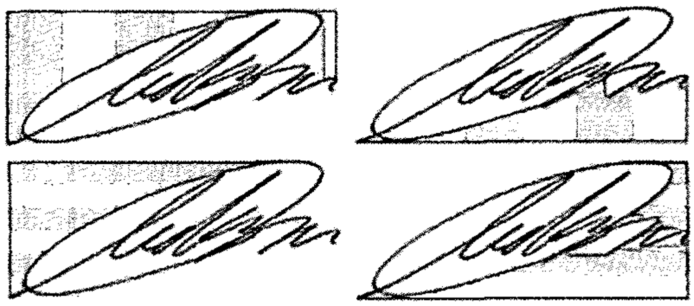

Fig. 7 *Extraction of the ET1 peripheral feature*

The area of each shaded strip constitutes one feature value of the resulting feature vector. Altogether a 24-dimensional feature vector is extracted in this example

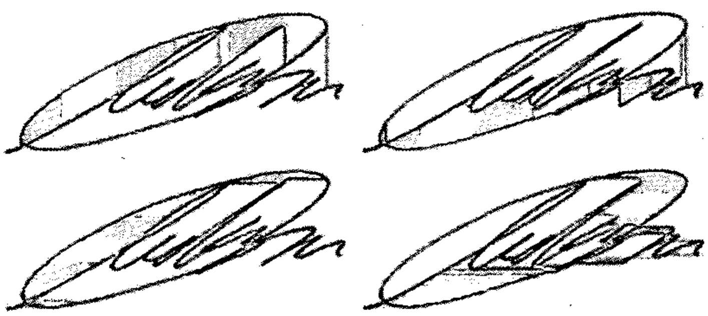

Fig. 8 *Extraction of the DT12 differential peripheral feature*

The area of each shaded strip constitutes one feature value of the resulting feature vector. Altogether a 24-dimensional feature vector is extracted in this example

In the test phase, given a test signature with feature vector $\boldsymbol{F}_t$, the Mahananobis distance $d(\boldsymbol{F}_t, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ is used to measure the dissimilarity between the input test signature and the set of training signatures according to:

$$d = \sqrt{(\boldsymbol{F}_t - \boldsymbol{\mu})^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\boldsymbol{F}_t - \boldsymbol{\mu})} \tag{3}$$

The test signature is accepted as authentic if the dissimilarity is less than a given threshold; otherwise, it is considered as a forgery. The threshold is selected to minimise the average error rate of the whole system. Two types of errors are defined: the type I error rate, or the false rejection rate (FRR), and the type II error rate or false acceptance rate (FAR). The average error rate is defined to be the average of FRR and FAR.

As explained earlier, when the number of training samples is small compared with the feature vector dimension, the estimated covariance matrix as given by (2) is not reliable, and may even be singular. If the matrix is singular, its inverse does not exist, so that the distance measure in (3) cannot be computed. The proposed method for generating additional training samples from existing ones is employed. The expanded training set is then used for estimating the statistics according to (1) and (2).

4 Experimental results

The proposed methods were evaluated on a database of 1320 authentic signatures and 1320 forgeries. The authentic signatures were collected from 55 volunteers over a period of one month, with each person contributing 24 signatures. Twelve other persons were recruited as forgers. Each forger produced 110 forgery signatures (two forgeries for each of the 55 volunteers). The forgers were instructed to briefly study each genuine signature before imitating it. The overall quality of the forgeries was average. The signatures were digitised by a scanner at a resolution of 300 dots per inch.

4.1 Signature verification without additionally generated training samples

In the first experiment, the effectiveness of the ET1 and DT12 features for signature verification was evaluated. The proposed elastic matching method for generating additional training samples was not employed. In the determination of the false rejection rate, due to the limited number of training samples, the leave-one-out method was adopted to maximise the use of the available authentic samples. When the number of training samples is less than the feature vector dimension, the estimated covariance matrix in (2) is singular. Hence, the distance d in (3), which involves the non-existent inverse of the matrix, is not computable. To enable the distance to be computed, the off-diagonal elements of the estimated covariance matrix were set to zero. Hence, only the variances of each vector dimension were used and the covariance between different dimensions was ignored.

Experiments with feature dimensions from 8 to 120 were performed. The best result was achieved with a feature dimension of 56, with an error rate of 15.6%, as shown in Table 1.

Table 1: Error rates of the proposed ET1 and DT12 features for signature verification without employing additionally generated training samples

Feature dimension	False rejection rate, %	False acceptance rate, %	Average error rate, %
8	19.9	23.0	21.5
16	17.2	18.4	17.8
32	17.1	16.4	16.7
48	17.0	15.1	16.0
56	**14.7**	**16.5**	**15.6**
64	15.6	16.1	15.8
80	17.6	14.7	16.1
96	17.0	15.3	16.1
120	16.4	16.5	16.5

4.2 Signature verification with additionally generated training samples

In the second experiment, the proposed elastic matching method for generating additional training samples was adopted. Each time, two signature samples were selected from the training set and the two-dimensional (2-D) elastic matching algorithm described in Section 2.1 was used to match the two patterns. After matching each pair of authentic training signatures, an additional signature was generated by the procedure described in Section 2.2. Examples of generated signatures are shown in Figs. 3 to 6.

Experiments were then performed to test the usefulness of the generated additional training samples for improving the verification accuracy of the system. To compare the results with the previous experiments (reported in the preceding Section), the leave-one-out method was still adopted in the determination of the false rejection rate. In each round of training and testing (total 24 rounds), of the 24 authentic signatures from each writer (total 55 writers), 23 samples were used for training and one sample was used for testing. Each time, two samples were drawn from this set of 23 training samples. Elastic matching was performed on this pair of samples and one additional sample was generated by deforming one of the samples. Afterwards, a second additional sample was generated by deforming the other sample. With 23 training samples, 253 ($={}_{23}C_2$) different pairs could be selected. Therefore, there were a total of $2 \times 253 = 506$ additionally generated samples plus the original 23 authentic signatures for training. For each writer, these 529 training samples were used to compute the class mean and class covariance matrix according to (1) and (2). The process was repeated for each of the 55 writers.

In the determination of the false acceptance rate, the training set for each of the 55 writers consisted of all of the 24 available authentic signatures as well as the $2 \times 276 = 552$ additionally generated samples, and the test set consisted of all the forgery samples.

During testing, the Mahalanobis distance given by (3) was employed to determine the authenticity of the test sample. The experimental results are given in Table 2, along with the results of the preceding Section for comparison. With the use of additionally generated samples for training and with a feature dimension of 24, the verification error rate was 11.4%. In the previous case in which these additional samples were not generated, the best error rate was 15.6%. The improvement was significant.

Table 2: Average verification error rates for experiments with or without using additionally generated training samples, and with feature dimensions ranging from 8 to 56

Training method	Form of covariance matrix	Error rate for various feature dimensions 8	24	40	56
Without generated samples	diagonal	21.5%	16.8%	16.4%	**15.6%**
With generated samples	diagonal	19.0%	14.8%	14.5%	14.4%
With generated samples	full matrix	15.0%	**11.4%**	12.3%	13.3%

For the first two rows, the off-diagonal elements of the class covariance matrices in (2) are set to zero. For the third row, the full covariance matrices are used

4.3 Comparison with other feature extraction methods

It is difficult to compare the performance of different signature verification systems because different systems use different signature data sets. Hence, to compare the proposed method with other published works, two published methods were implemented and tested with the same database as that used in this study [2, 4]. The average error rates of Ammar's [2] and Sabourin's [4] methods were 22.8% and 17.8%, respectively. For the proposed method, the error rates were 15.6% and 11.4% for the cases of using or not using generated samples for training, respectively. The results are summarised in Table 3. This shows that the proposed method is quite favourable compared with other methods.

4.4 Comparison with other covariance matrix estimation methods

There are different approaches to tackle the problem of having not enough samples for training. The approach adopted in this study is to expand the training set by generating additional samples from existing samples. Another approach does not generate additional training samples, but obtains an alternative estimate of the class covariance matrix directly from the original training set with the objective of minimising the verification error rate. Instead of using the maximum likelihood estimate as in (2), the matrix is assumed to be in the form of a weighted sum of various matrices and the best solution is obtained by optimisation procedures. The RDA [5] and LOOC [6] algorithms fall into this category.

To compare the proposed approach of generating additional samples with existing matrix estimation methods, the LOOC [6] algorithm was also implemented and tested on the same database as in this study. The same ET1 and DT12 features as explained before were employed. For the method proposed in this study, the covariance matrix was computed using (2) with additionally generated training samples. For the LOOC approach, the covariance matrix was computed according to the method given in [6].

Experimental results are given in Table 4. The lowest error rate for the LOOC [6] method was 12.5%, while the proposed method gave an error rate of 11.4%. Hence, the proposed method for tackling the problem of insufficient training samples performed better than the other method.

Table 3: Comparison of the performance of the proposed method with the methods given in [2] and [4]

Method	Average error rate, %
Global shape features [2]	22.8
Extended shadow code [4]	17.8
Proposed method (without generated samples)	15.6
Proposed method (with generated samples)	11.4

4.5 Comparison with human operators

Three postgraduate students not associated with the project were recruited to perform the signature verification task. On the computer screen, two signatures were displayed each time: (i) an authentic signature for reference, and (ii) a signature with the authenticity unknown to the operator. The operator had to either accept or reject the signature in question. The operator was told the fact that the probability of each unknown signature being authentic was 0.5. The average error rate of the three volunteers was 23.7%. Compared with the error rate of 11.4% for the proposed method, the human operators were 12.3% worse, as summarised in Table 5. However, it should be noted that the three volunteers were not trained for the job of signature verification. The performance of professional operators could be quite different.

Table 4: Comparison of the proposed method for generating additional training samples with the existing LOOC covariance matrix estimation method [6]

Training method	Error rate for various feature dimensions 8	24	40	56
LOOC [6]	15.7%	13.4%	**12.5%**	**12.5%**
Proposed method	15.0%	**11.4%**	12.3%	13.3%

Table 5: Comparison of the performance of the proposed method with that of three untrained volunteers

Signature verification method	Average error rate, %
Volunteer 1	22.4
Volunteer 2	25.3
Volunteer 3	23.4
Proposed method	11.4

5 Discussions and conclusions

The realistic problem of insufficient training samples in offline signature verification was tackled. The proposed method was to generate additional training samples from the existing training set by an elastic matching technique. The verification error rate was much improved by incorporating the generated samples into the original training set. The method also outperformed other techniques which use optimisation approaches to estimate the class covariance matrix instead of generating additional training samples [5, 6].

Peripheral features which describe the external shape and internal structures of the signature pattern were employed for signature verification. Although these features were originally used for character recognition [7], results showed that they were also well suited for signature verification. When tested on the same database, the proposed method performed better than other existing methods [2, 4].

Three independent untrained volunteers carried out the same signature verification task manually. Their average error rate was much higher than of the proposed method.

In this paper, the elastic matching method was employed to generate additional training samples. An alternative approach is to use the matching result to determine a distance measure between a template authentic signature and an unknown signature, and directly use this distance for verification. For example, the distance can be formulated as a function of the displacement vectors as illustrated in Fig. 2*b*.

6 Acknowledgment

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