



A new signature verification technique based on a two-stage neural network classifier

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Abstract

This paper presents a new technique for off-line signature recognition and verification. The proposed system is based on global, grid and texture features. For each one of these feature sets a special two stage Perceptron OCON (one-class-one-network) classification structure has been implemented. In the first stage, the classifier combines the decision results of the neural networks and the Euclidean distance obtained using the three feature sets. The results of the first-stage classifier feed a second-stage radial base function (RBF) neural network structure, which makes the final decision. The entire system was extensively tested and yielded high recognition and verification rates. © 2001 Elsevier Science Ltd. All rights reserved.

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1. Introduction

As available computing power eventually increases and computer algorithms become smarter, tasks that a few years ago seemed completely unfeasible, now come again to focus. This partly explains why a considerable amount of research effort is being recently devoted in designing algorithms and techniques associated with the problems like human handwritten signature recognition and verification.

A signature recognition and verification system (SRVS) is a system capable of efficiently addressing two individual but strongly related tasks: (a) identification of the signature owner, and, (b) decision whether the signature is genuine or forger. Depending on the actual needs of the problem at hand, SRVSs are often categorized in two major classes: on-line SRVSs and off-line SRVSs. While for systems belonging to the former class, only digitized signature images are needed, for systems in the latter class, information about the way the human hand creates the signature such as hand

speed and pressure measurements, acquired from special peripheral units, is needed.

During the last few years, several on-line Parizeu and Plamondon, 1990; Brault and Plamondon, 1993; Lee et al., 1996) and off-line (Qi and Hunt, 1994; Yedekcoglu et al., 1995; Han and Sethi, 1996; Droughard et al., 1996; Bajaj and Chaudhury, 1997; Huang and Yan, 1997) SRVSs have been proposed. In the off-line category, Qi and Hunt (1994) proposed a SRVS that is based on global and grid features in conjunction with a simple Euclidean distance classifier. Yedekcoglu et al. (1996) developed a technique based on thickened templates that can be utilized as an initial face of a SRVS in order to reject signatures that are completely unmatched. Han and Sethi (1996) proposed a signature retrieval and identification system based on geometric and topologic features. Droughard et al. (1996) used directional probability density function in conjunction with backpropagation-trained neural networks. Bajaj and Chaudhury (1997) used multiple neural networks supplied by three sets of global features, including projection moments. Huang and Yan (1997) use geometric features in combination with a neural network classifier. However, the experimental results were based on a small number of samples. Ramesh and

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Murty (1999) propose a system for off-line signature verification, which consists of four subsystems based on geometric features, moment representations, envelope characteristics and wavelet features.

In this paper, a novel approach for off-line signature recognition and verification is proposed. The presented system is based on three powerful feature sets in combination with a multiple-stage neural-network-based classifier (Fig. 1). The novelty of the system lies mainly on the structure of the classifier and the way that it is used. The neural network classifier is arranged in two stages.

We have understood that for a SRVS to be functional in practical applications, the ability to easily add/remove signatures from new/obsolete owners to its database must be inherent. Our approach towards this goal is to implement the structure of the neural network classifier is a one-class-one-network scheme. That is for each signature owner an individual classifier is being implemented. Each time signatures from a new owner are added to the SRVS database, only a small, fixed-size, neural-network-based classifier must be trained.

Moreover, to farther overcome training difficulties stemming from the feature set size, the proposed feature set is divided into three individual feature groups of different physical meaning. For each of the resulting three feature groups, an individual multi-layer perceptron (MLP) neural network is implemented. These three small and fixed size neural networks for each signature owner constitute the first stage of the classifier. It is a task of the second-stage classifier, a radial basis functions (RBF) neural network to combine the results of the first stage to make the final decision of weather the presented to the system signature, belongs to a candidate owner or not.

The experimental results confirm the effectiveness of the proposed structure and show its ability to yield high recognition and verification rates.

2. Preprocessing

The preprocessing stage is divided into four different parts: noise reduction, data area cropping, width normalization and signature skeletonization.

2.1. Noise reduction

Before any further processing takes place, a noise reduction filter is applied to the binary scanned image. The goal is to eliminate single white pixels on black background and single black pixels on white background. In order to accomplish this, we apply a 3×3 mask to the image with a simple decision rule: if the number of the 8-neighbors of a pixel that have the same

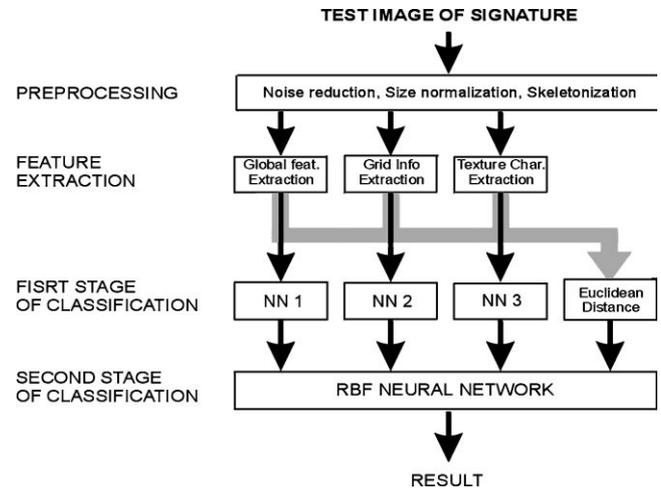


Fig. 1. Structure of the system.

color with the central pixel is less than two, we reverse the color of the central pixel.

2.2. Data area cropping

The signature area is separated from the background by using the well-known segmentation method of vertical and horizontal projections (Gonzalez and Wintz, 1987). Thus, the white space surrounding the signature is discarded.

2.3. Width normalization

The image size is adjusted so that the width reaches a default value while the height-to-width ratio remains unchanged.

2.4. Skeletonization

A simplified version of the skeletonization technique described by Lam and Suen (1991) is used. The simplified algorithm used here consists of the following three steps:

Step 1: Mark all the points of the signature that are candidates for removing (black pixels that have at least one white 8-neighbor and at least two black 8-neighbors pixels).

Step 2: Examine one by one all of them, following the contour lines of the signature image, and remove these as their removal will not cause a break in the resulting pattern.

Step 3: If at least one point was deleted go again to Step 1 and repeat the process once more.

Fig. 2. shows an example of this skeletonization technique. Skeletonization makes the extracted features invariant to image characteristics like the qualities of the pen and the paper the signer used, and the digitizing method and quality.

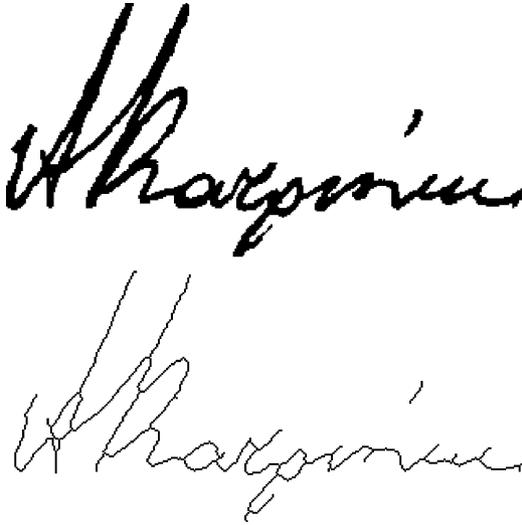


Fig. 2. Example of the skeletonization algorithm.

3. Feature extraction

The choice of a powerful set of features is crucial in optical recognition systems. The features used must be suitable for the application and for the applied classifier. In this system, three groups of features are used categorized as global features, grid information features and texture features.

While global features provide information about specific cases concerning the structure of the signature, grid information and texture features are intended to provide overall signature appearance information in two different levels of detail. For grid information features, the image is segmented in 96 rectangular regions. Only the area (the number of signature points) in each region is utilized in order to form the grid information feature group. For the texture feature group to be formed, a coarser segmentation scheme is adopted. The signature image is segmented in only six rectangular areas, while, for each area, information about the transition of black and white pixels in the four different directions is used.

3.1. Global features

Signature height. The height of the signature image, after width normalization, can be considered as a way of representing the height-to-width ratio.

Image area. The number of black (foreground) pixels in the image. In skeletonized signature images, it represents a measure of the density of the signature traces.

Pure width. The width of the image with horizontal blank spaces removed (Qi and Hunt, 1994).

Pure height. The height of the signature image after vertical blank spaces removed.

Baseline shift. The deference, between the vertical centers of gravity of the left and the right part of the image. It was taken as a measure for the orientation of the signature.

Vertical center of the signature. The vertical center C_y is given by

$$C_y = \frac{\sum_{y=1}^{y_{\max}} y \sum_{x=1}^{x_{\max}} b[x, y]}{\sum_{x=1}^{x_{\max}} \sum_{y=1}^{y_{\max}} b[x, y]} \quad (1)$$

Horizontal center of the signature. The horizontal center C_x is given by

$$C_x = \frac{\sum_{x=1}^{x_{\max}} x \sum_{y=1}^{y_{\max}} b[x, y]}{\sum_{x=1}^{x_{\max}} \sum_{y=1}^{y_{\max}} b[x, y]} \quad (2)$$

Maximum vertical projection. The vertical projection of the skeletonized signature image is calculated. The highest value of the projection histogram is taken as the maximum vertical projection.

Maximum horizontal projection. As above, the horizontal projection histogram is calculated and the highest value of it is considered as the maximum horizontal projection.

Vertical projection peaks. The number of the local maxima of the vertical projection histogram.

Horizontal projection peaks. The number of the local maxima of the horizontal projection histogram.

Global slant angle. The image is rotated from -30° to 40° with a step of 1° . For each step, the number of vertical 3-pixel connections is calculated. The angle that has the most vertical 3-pixel connections is the global slant angle (Qi and Hunt, 1994).

Local slant angle. The image is rotated in a similar way as above. For each angle of rotation, the vertical projection histogram is calculated and the 70 highest values of the histogram are summed. The angle that presents the highest summation is the local slant angle (Qi and Hunt, 1994).

Number of edge points. An edge point is defined as a signature point that has only one 8-neighbor.

Number of cross points. Cross point is a signature point that has at least three 8-neighbors.

Number of closed loops. The number of closed loops can be defined as

$$CL = 1 + \frac{EL - EP}{2} \quad (3)$$

with EP denoting the number of edge points and EL the number of extra departures, defined as

$$EL = \sum_{\text{All cross points}} [(\text{Number of 8-neighbors}) - 2]. \quad (4)$$

It is to be noted that if the skeletonized signature image is not compact, that is, the signature is divided

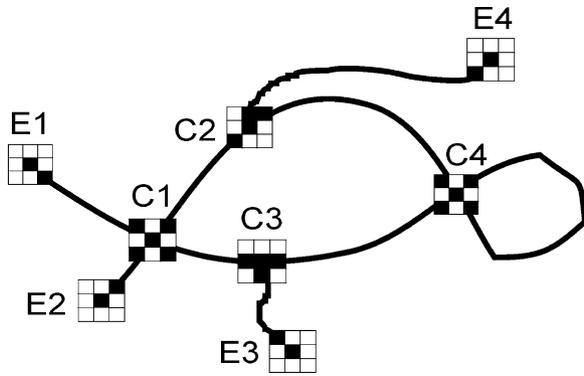


Fig. 3. Examples of corner (C1, C2, C3, C4) and edge (E1, E2, E3, E4) points.

into two or more non overlapping segments, the number of closed loops, as defined above, has no physical interpretation. Even in that case, this number is characteristic for each signature and describes the amount of complexity that the signature lines involve.

Some examples of cross and edge points are shown in Fig. 3.

3.2. Grid information features

The skeletonized image is divided into 96 rectangular segments (12×8), and for each segment, the area (the sum of foreground pixels) is calculated. The results are normalized so that the lowest value (for the rectangle with the smallest number of black pixels) would be zero and the highest value (for the rectangle with the highest number of black pixels) would be one. The resulting 96 values form the grid feature vector.

A representation of a signature image and the corresponding grid feature vector is shown in Fig. 4. A black rectangle indicates that for the corresponding area of the skeletonized image we had the maximum number of black pixels. On the contrary, a white rectangle indicates that we had the smallest number of black pixels.

3.3. Texture features

To extract the texture feature group, the co-occurrence matrices of the signature image are used. In a gray-level image, the co-occurrence matrix $P_d[i, j]$ is defined by first specifying a displacement vector $d = (dx, dy)$ and counting all pairs of pixels separated by d and having gray level values i and j . In our case, the signature image is binary and therefore the co-occurrence matrix is a 2×2 matrix describing the transition of black and white pixels (Haralick and Shapiro, 1992; Jain et al., 1995). Therefore, the co-occurrence matrix $P_d[i, j]$



Fig. 4. The grid feature vector of a signature.

is defined as

$$P_d[i, j] = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}, \quad (5)$$

where p_{00} is the number of times that two white pixels occur, separated by d . p_{01} is the number of times that a combination of a white and a black pixel occurs, separated by d . p_{10} is the same as p_{01} . p_{11} is the number of times that two black pixels occur, separated by d .

The image is divided into six rectangular segments (3×2). For each region the $P_{(1,0)}$, $P_{(1,1)}$, $P_{(0,1)}$ and $P_{(-1,1)}$ matrices are calculated and the p_{01} and p_{11} elements of these matrices are used as texture features of the signature. The above procedure sums up to 48 features (six segments \times four matrices \times two elements).

4. The signature database

For training and testing of the SRVS many signatures are used. The results given in this paper are obtained by using a signature master database of about 2000 signatures. The signatures were taken from 115 persons (15–25 signatures from each).

For training the system, two subsets, taken from the master set, of about 1000 and 500 signatures were used. The first subset (TRS1) was used to train the first-stage classifier while the second subset (TRS2) was used to train the second-stage classifier. The performance of the system was checked by the use of the remaining subset (TS) of 500 signatures.

In order to make the system robust to intra-personal variations and to extract worst-case classification rates, the signers were asked to use as much variation in their signature sizes and shapes as they should ever use in real circumstances. Whenever it was feasible (for about 10 of the 147 persons), the signature acquisition was performed in more than one phases (4 to 5 signatures per



Fig. 5. Examples of signatures from various owners.

day without letting the signer see the signatures he/she has already given in previous phases).

Examples of signatures are shown in Fig. 5.

5. Classification

Multi-layer perceptron (MLP) neural networks are among the most commonly used classifiers for pattern recognition problems. Despite their advantages, they suffer from some very serious limitations that make their use, for some problems, impossible. The first limitation is the size of the neural network. It is very difficult, for very large neural networks, to get trained. As the amount of the training data increases, this difficulty becomes a serious obstacle for the training process.

The second difficulty is that the geometry, the size of the network, the training method used and the training parameters depend substantially on the amount of the training data. Also, in order to specify the structure and the size of the neural network, it is necessary to know a priori the number of the classes that the neural network

will have to deal with. Unfortunately, when talking about a useful SRVS, a priori knowledge about the number of signatures and the number of the signature owners is not available.

The proposed SRVS confronts these problems by reducing the training computation time and the size of the neural networks used. This is achieved by:

- Reduction of the feature space. The feature set is split to three different groups, i.e., global features, grid features and texture features. Due to the different nature and the uncorrelation of the three feature sets, the combination of the three feature vectors covers the required feature information.
- Reduction of the necessary training samples. This is achieved because each neural network corresponds to only one signature owner. Specifically, during the first stage of classification, multiple but fixed-size neural networks are used (Figs. 1 and 6). In Fig. 1, each one of the neural-networks NN1, NN2, NN3 specializes in signatures of only one person. For practical systems, this approach offers another significant

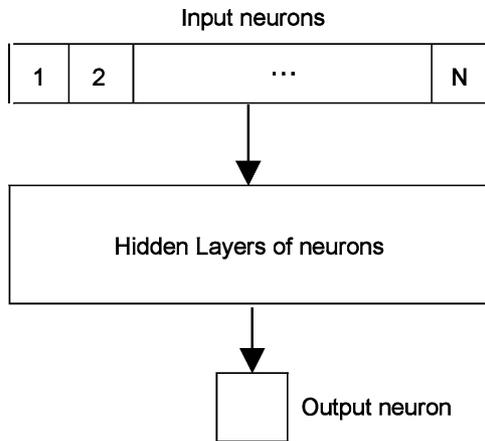


Fig. 6. The structure of a single OCON (one-class-one-network) neural network.

advantage: each time we want to add a set of signatures (a new person) to the systems database, we only have to train three new small neural networks (one for each set of features). It is not necessary to retrain a very large neural network, which is of course a much more difficult situation.

Due to the use of many neural networks, it is necessary to apply a training algorithm that can train them efficiently, avoiding local minima. The ALOPEX algorithm (Pandya and Macy, 1995) was chosen for this task. Due to its stochastic nature, it presents a remarkable tendency to avoid local minima. The main drawback of the ALOPEX algorithm is its convergence time, which for problems having no local minima but strong global minimum is longer than the time the back propagation algorithm needs to converge. This drawback was not of much importance for our problem because of the small dimensionality of the neural networks used.

In conjunction with the three neural network structures, a simple MED classifier, utilizing all the three groups of features together, is applied.

The results of the above structures were propagated to the second stage of the classification where an RBF network was used to make the final decision.

5.1. First stage of classification

The first stage of classification is based on the use of three MLPs, one for each group of features. All features are normalized within the region $[0, 1]$. For each owner in TRS1 all the three MLPs are trained individually using the ALOPEX algorithm with a fixed number of iterations. The training set, consists of all the signatures in TRS1 of the specific owner and a number of 150 random signatures among other owners in TRS1. The

resulting weights are stored separately for each owner in a special database.

As shown in Fig. 1, an Euclidean distance metric is used in conjunction with the three neural networks described above. Although the feature distributions within the data do not provide any clear evidence that signature classes were completely separable by such a metric, practice showed that:

- There are some cases where one or more neural networks are misled to incorrect output due to either feature distribution overlaps among classes or insufficient training. While, for the former case very little can be done, for the latter case, the Euclidean distance metric provides an extra vote towards the correct direction.
- While the Euclidean distance does not perform well in all cases, its output hardly is such that can lead the second stage of the classification structure to incorrect results.
- Since the Euclidean distance block is the only one supplied by all features groups, it enables the system to have simple and quite stable metric of the distribution of classes in the whole feature space.

Fig. 1 demonstrates the structure of the classifier. The first neural network NN1 has 16 inputs (the global features), the second NN2 96 inputs (12×8) and the third NN3 48 inputs ($3 \times 2 \times 4 \times 2$). The Euclidean distance block has 160 inputs ($16 + 96 + 48$). Each neural network has only one output neuron. Output “1” indicates that the input is recognized. Output “0” indicates that the input is not recognized.

Each of the four blocks propagates its result to a second-stage classification RBF network, where the final decision is being made.

5.2. Second stage of classification

The four classifiers used in the first stage produce outputs in the range $[0, 1]$. Given a test signature and a candidate owner, the output of each one of these classifiers should be close to “1” if the signature is similar to the signatures of the candidate owner in the training database. On the contrary, the output should be close to “0” if the signature does not match with a prototype one and therefore should be rejected.

To make the system able to combine the knowledge offered by the four neural networks of the first stage, one could use a weighted average of these four classifiers in combination with a proper thresholding technique. In this work an RBF neural network is used in order to have the final decision. The RBF neural networks are feed-forward architectures with a hidden non-linear layer and a linear output layer. The structure of the network used here is shown in Fig. 7. The network has four inputs (fed by the outputs of the first-stage

classifiers), a hidden layer with two non-linear neurons and a simple output linear neuron.

The RBF neural network of the second stage is trained after training of all the neural networks of the first stage. The RBF network does not use the signatures of TRS1 for training, because they are already used as prototype signatures in the first stage. Thus, a new training set TRS2 is used, which is unknown in the first stage.

The activation functions of the two hidden neurons are chosen to be Gaussians, so they are characterized by their mean vectors (centers of the two classes) $\mathbf{m}_1, \mathbf{m}_2$ and the covariance matrices C_1, C_2 . Thus, the activation function of the i th hidden neuron for an input \mathbf{x}_j is given as

$$g_i = \exp\left(-\frac{1}{2}(\mathbf{x}_j - \mathbf{m}_i)^T \Sigma_i^{-1}(\mathbf{x}_j - \mathbf{m}_i)\right), \quad i \in \{1, 2\}, j \in \{1, 2, \dots, N_{tr}\}, \quad (6)$$

where N_{tr} is the number of the training examples and $\frac{1}{2}\Sigma_i^{-1} = C_i^T C_i$.

In the RBF network the hidden layer neurons are fully connected to the output neuron, and its response is given as

$$y(x_j) = -\lambda_0 + \lambda_1 g_1(\mathbf{x}_j) + \lambda_2 g_2(\mathbf{x}_j) \quad (8)$$

or

$$\mathbf{Y} = \mathbf{G}\mathbf{A} \quad (9)$$

with

$$\mathbf{Y} = \begin{bmatrix} y(x_1) \\ \dots \\ y(x_{N_{tr}}) \end{bmatrix},$$

$$\mathbf{G} = \begin{bmatrix} -1 & g_1(x_1) & g_2(x_1) \\ \dots & \dots & \dots \\ -1 & g_1(x_{N_{tr}}) & g_2(x_{N_{tr}}) \end{bmatrix},$$

$$\mathbf{A} = \begin{bmatrix} \lambda_0 \\ \lambda_1 \\ \lambda_2 \end{bmatrix}. \quad (10)$$

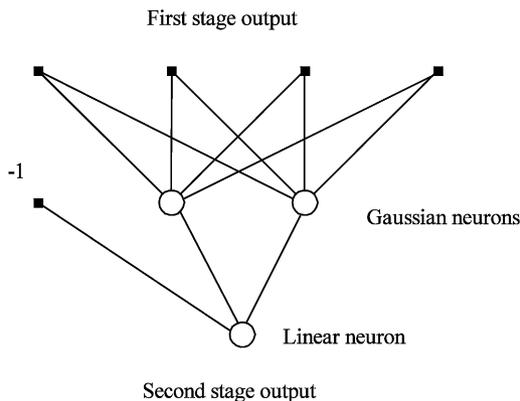


Fig. 7. The RBF neural network serving as second-stage classifier.

Training the RBF network means estimation of $\mathbf{m}_1, \mathbf{m}_2, C_1, C_2, \lambda_0, \lambda_1, \lambda_2$.

The $\mathbf{m}_1, \mathbf{m}_2, C_1, C_2, \Sigma_1, \Sigma_2$ are calculated directly from the training data while the $\lambda_0, \lambda_1, \lambda_2$ are obtained as

$$\mathbf{A} = (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \mathbf{Y}. \quad (11)$$

To solve the above equation, \mathbf{G} is easily computed from Eq. (6) while vector \mathbf{Y} is defined from Eq. (9), with

$$y(\mathbf{x}_j) = \begin{cases} 1 & \text{if the signature with first stage output } \mathbf{x}_j \\ & \text{should be accepted,} \\ -1 & \text{if the signature with first stage output } \mathbf{x}_j \\ & \text{should be rejected.} \end{cases} \quad (12)$$

6. The training phase

The training of the system includes the following two steps.

Step 1: Train the first-stage classifier

This task consists of training the three neural networks for each person in the TRS1. The TRS1 consists of 1000 signature images randomly selected from the master set of 2000 signature images. There are available signatures from 115 different persons and so we have to train $115 \times 3 = 345$ different but small size neural networks.

Each neural network corresponds to a specific owner, and therefore, all of his features are considered as positive (prototype) training examples. As negative examples, features from 150, randomly selected signatures of other owners in TRS1 are used. All the neural networks are trained with a fixed number of iterations and their weights coefficients are stored.

Step 2: Train the second-stage classifier.

To train the second-stage classifier the signatures from TRS1 cannot be used because they already have been applied to the first stage classifier. Thus, a second training set, TRS2, is used. TRS2 consists of 500 signature images randomly selected from the remaining 1000 signatures in the master set.

For each one of the 500 signatures, one positive example is formed by telling the classifier of stage one to examine for the correct owner (to use the neural networks of the correct owner) and 114 negative examples. Doing this, 57,500 training examples (500 positive and 57,000 negative) are formed and used to train the RBF neural network.

7. Testing phase and results

According to the above analysis, when the system is asked to decide whether an unknown signature image belongs to a particular person in the database the following steps are followed.

- The unknown signature image passes through the pre-processing and feature extraction stages.
- The three sets of features are applied to the inputs of all of the three specialized Perceptron neural networks. The networks are run forward so that we get outputs for all of them.
- The Euclidean distance between the 160 features (all the three sets) of the unknown signature image and the features of each signature in the TRS1 that belongs to the candidate person is calculated. The average Euclidean distance is then extracted. For example, the Euclidean norm (D_N) between the feature vector of the unknown image X_T and the feature vector of the N th signature in the database X_N is given from the following equation:

$$D_N = \sqrt{\sum_{i=1}^{160} (X_{Ti} - X_{Ni})^2}. \quad (13)$$

The outputs of the three neural networks and the average Euclidean distance are taken as the inputs of the second-stage classifier (the RBF neural network). The RBF neural network is then ran forward. If the output is positive, the given signature belongs to the candidate person. If not, it does not belong to the candidate person.

For the performance testing of the system, the remaining 500 signatures in the master set are used (unknown both to the first- and to the second-stage classifiers). This set is called TS and the system is tested by two different scenarios: the verification scenario and the recognition scenario.

7.1. The verification scenario

For each signature in TS, we queried the system 115 times, one time for each owner. The TS contained 500 signature images and that made $115 \times 500 = 57,500$ testing cases.

The possible cases are

Correct acceptance. The system was asked if the signature belonged to the correct owner and the response was positive.

False rejection. The system was asked if the signature belonged to the correct owner and the response was negative.

False acceptance. The system was asked if the signature belonged to a false owner and the response was positive.

Table 1

Cases that should be accepted	500
Cases that should be rejected	57,000
Accepted	1485
Rejected	56,015
Correct acceptances	485 (97%)
False rejections	15 (3%)
Correct rejections	51,211 (90.019%)
False acceptances	5689 (9.81%)

Table 2

Cases	500
Correct classifications	404 (80.81%)
False classifications	96 (19.19%)

Correct rejection. The system was asked if the signature belonged to a false owner and the response was negative.

Table 1 summarizes the results obtained in the verification stage.

7.2. The recognition scenario

For each signature in TS, we queried the system 115 times (one time for each owner). The system proposes as the signature owner the owner that gives the maximum output value of the RBF neural network.

In summary, the results obtained are given in Table 2.

8. Conclusions and remarks

This paper proposes a new off-line signature verification and recognition technique. The entire system is based on 160 features grouped to three subsets and on a two-stage neural network classifier that is arranged in an-one-class-one-network scheme. During the training process of the first stage, only small, fixed-size neural networks have to be trained, while, for the second stage the training process is straightforward.

In designing the proposed system, most of our efforts were towards of embodying most of the intelligence to the structure of the system itself. No feature reduction process was used and the basic rule of thumb in deciding which features to include and which not was “use all features and leave the neural networks decide which of them are important and which are not”. Usually, such a rule leads to very large and complicated neural networks, very difficult to get trained. The innovation of the proposed system is the categorization of the features into groups and the adoption of a two-stage structure. We showed that such a structure leads to small, easily trained classifiers without hazarding performance by leaving out features that may be useful to the system.

Besides the advantage of easily training, the proposed structure offers the substantial benefit of the ability to expand with new signatures without having to retrain the entire system from the starting point. That is, no a priori knowledge concerning the number of persons and the number of signatures is required at design time.

It is also to be noted that the performance of the system, as it is illustrated by the recognition and the verification rates that we presented, expresses a worst-case scenario. The signers were asked to use as much variation in their signatures as they should ever use under real circumstances. The type of the features and the classifier used were proven to offer to the entire system independence of the signature type and size.

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