Nov. 30

International Journal of advanced studies in Computer Science and Engineering
IJASCSE, Volume 3, Issue 11, November 2014

High-Performance Signature Recognition Method using SVM

Saeid Fazli
Research Institute of Modern Biological Techniques
University of Zanjan

Shima Pouyan
Electrical Engineering Department
University of Zanjan
Zanjan, Iran

Mahnaz Moghaddam
Electrical Engineering Department
University of Zanjan
Zanjan, Iran

***Abstract*—the signature is widely used in many cases for personal verification and resulting a demand for an automatic recognition system. In this paper we present a system for offline signature recognition. The proposed system consists of image preprocessing, feature extraction and classification steps. preprocessing step include noise reduction, background elimination, rotation, thinning, cropping and width normalization. For noise reduction we use Gaussian filter which is considered the ideal time domain filter. The classification step contains three methods for classifying: nearest neighbor, neural network and support vector machine. We also compare SVM performance with neural network and KN. Our results show that due to the low number of features the SVM, which achieves up to 95.625% correct recognition rate, outperforms Neural Network and KN.**

Keywords— preprocessing; feature extraction; nearest neighbor; neural network; support vector machine

I. Introduction

Today, the identification and verification of identity, security and access control to resources is crucial. The first and most basic identification method is using a personal number private. The number of personnel may be missing or exploited. One attractive approach is the use of biological approaches. It is one of the oldest biological signed. Thus, detection and authentication for single sign on, somewhat safe, cheap and has been accepted in the community. However, defects such as low detection rate compared with other biological and non-linear changes in the size and time dependence and feels. Another problem is the difference between signature signing processes among different nationalities. For example, Europeans have signed their name is usually written with a particular method, while the Signature Persian contains collection of symbols and lines. Signature processing can be used for the purpose of identify or confirm the identity. For identify system should recognize that the signature belongs to whom. [1]

Handwritten signature recognition is divided into on-line and off-line recognition. In on-line recognition the signatures are collected using a tablet or other devices and in the off-line recognition signature images are written on a paper and obtained by a scanner or a camera. This project is an offline signature recognition system with 3 methods for classify nearest neighbors, neural network and SVM. The outline of this paper is as follows: the next section is about data and preprocessing in this section we also explain feature extraction methods and classification techniques and in section three we discuss about experimental results and in section four some conclusions are drawn.

II. Materials and Methods

Our methods are based on three stages: 1- data collection and preprocessing, 2- feature extraction, 3- data classification.

A. Materials

The signature database consists of 360 signature images, scanned at a resolution of 300 dpi. They are organized into 20 sets, and each set corresponds to one signature enrollment. Each volunteer was asked to sign his or her own signatures on a white paper 18 times.

Examples of the database image are shown in figure 1.

After scanning the images and before feature extraction we need preprocessing stage. The purpose in this phase is to make signatures standard and ready for feature extraction.

a. Noise reduction: We need to remove noises such as salt and pepper noise, ink spread noises, and the noise which is caused by scanner. Removal techniques, such as Gaussian-filtering is used to clean the initial image. Reducing these noises iincrease theaccuracyin the calculation of the district center

b. Background Elimination: the area of data must be cropped to extract features. At threshold is needed to capture signature from the background.

c. rotation: the moment of order 2 is calculated to find out the angle of rotation for the signatures and they are rotated in the clockwise around the center of the screw.this feature will make signatures in the same directions.

Figure 1. Examples of signatures from various owners

d. Thinning: Thinning is needed to make thickness of all data the same and making them one pixel thick so that the difference between pen pressures is eliminated.

e. data area cropping: the margin of image removed, before the first and after the last pixel of the Signature. Thus, the white space around the signature is eliminated.

f. width normalization: The signatures dimensions may be different. So we change the width and height values to make all ratio of height to width uniform.

Figure 2 shows the results of this process.

B. Feature extraction

Set of features is very important for recognition systems. The features used must be completely appropriate for the application and classifier. On the other hand in neural networks several vectors is needed as input so that the learning of network will be guaranteed.

The features must have three attributes of the following:

1. Signer must be largely indivisible due to the properties of the signatories.
2. Features must be constant. (thickness and pen friction).
3. Signer must sign in a standard way (neither too fast nor too slow).

Signature features that have been mentioned with regard to three properties, are derived as follows:

a. Global features

1. Signature height-to-width ratio: dividing signature height to signature width gives us a value which is usually equal for each person.
2. Signature Area: the number of pixels belong to the signature shows the density of signature .
3. The Trisurface feature: separating signatures into three part can make useful information about them and in some cases when the whole area of signatures are the same this feature can help recognition

We call these feature the Trisurface features.

4. Maximum horizontal and maximum vertical histogram: the horizontal and vertical histograms are calculated for each row and column and the row and column with the highest value is taken as maximum horizontal and maximum vertical histogram.
5. Horizontal and vertical center of the signature: To calculate the horizontal and vertical center of the signature, we used this way: scan column wise. For each column, those row index values, which are having black pixels, are added in the row_index_sum. Also a counter is incremented each time a black pixel in any row is found for that particular column. The same step is performed for all the columns. Cx=row_index_sum / total black pixels encountered. Scan row wise. For each row those column index values, having black pixels are added in column_index_sum. Also the counter is incremented each time a black pixel is encountered. The same step is performed for all the rows. Cy=column_index_sum/total black pixels encountered. Centre is calculated by formula (Cx+1) * total column in signature+Cy. This center as cell value is stored as center feature.
6. Edge point number of the signature: Edge point is the pixel of the signature whith only one neighbor, in 8-neighbor.

b. Texture features

1. Texture homogeneity H:

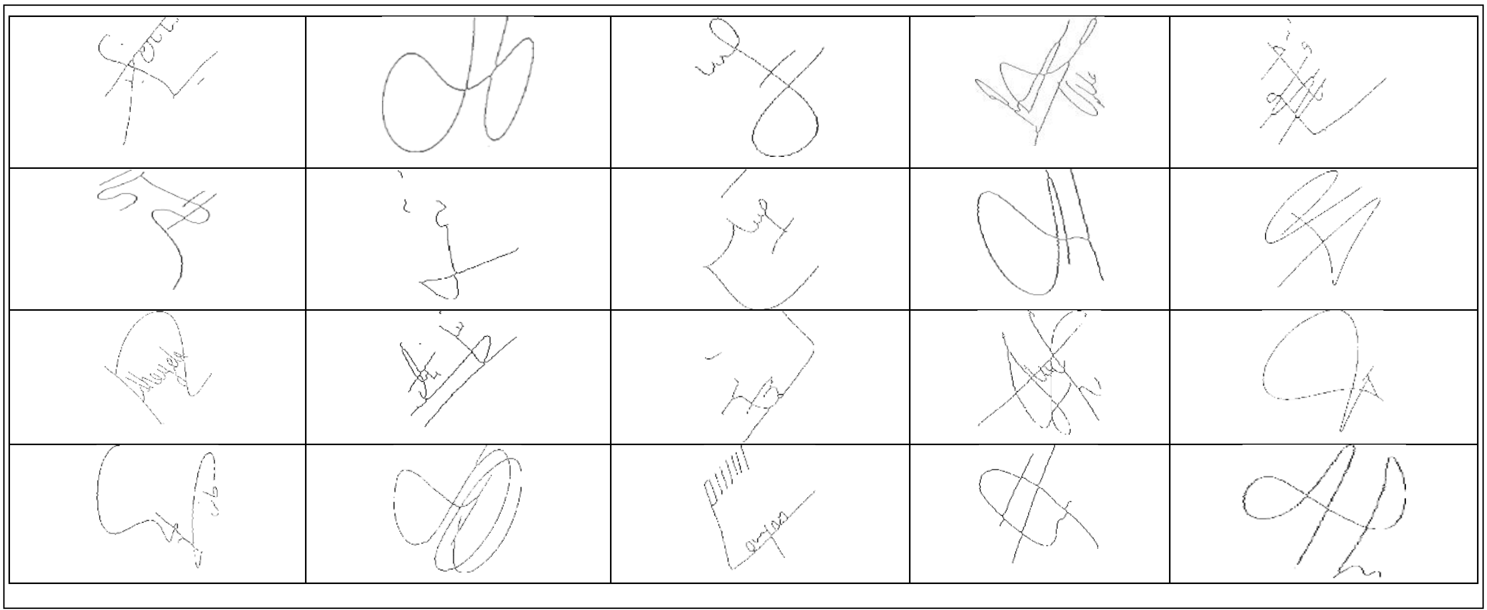

Figure 2. after preprocessing

$$H = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \qquad (1)$$

This feature shows the homogeneity or similarity of occurrence matrix with diagonal matrix.

2. Texture contrast C:

$$C = \sum_{i=0}^{G-1}\left\{n^2.\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)\right\}, |i-j| = n \quad (2)$$

It shows local intensity changes in each pixel and its neighbors.

3. Texture entropy E:

$$E = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j).\log\{P(i,j)\} \qquad (3)$$

This feature shows entropy of each images.

4. Texture correlation O:

$$O = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{i.j.P(i,j)-(m_i.m_j)}{\sigma_i.\sigma_j} \qquad (4)$$

It shows the correlation of each pixels with the neighboring pixels in the image.

c. Mask features

Mask features provide information about directions of the lines of the signatures. The angles of the signatures have interpersonal differences. In this system 4 different 3x3 mask features are used. Each mask is taken all around the signatures and the number of 3x3 parts of the signature, which are same with the mask, is calculated and so that the result is 4 features which define angles of 45, 90, 180 and 315.

These features have noted all differences of signatures to detect the signers in high percentage.

C. Classification

In signature classification we should specify that each signature is for whom. So the input of classification system is a signature and the output is the number of classes which mean the signer.
In the following the design of each classifier is written.

a. K nearest-neighbors

This classifier is the easiest one. When using the K nearest-neighbors classifier (K-NN), for each class of training set, we have ideal feature vectors. Then we measure the features of the unknown signature .To find out that this signature is for which class we measure the similarity with each class. 20% of the input data is used as validation data to find out the best value for K and distance factor.

Table 1. shows the errors of validation data for different values of K and different methods of distance factors.
As it is seen in the table the minimum error is happened in two conditions: distance factor= Correlation with K=3, and distance factor = City block and K= 7.For low calculation in test part we use distance factor= Correlation with K=3.

TABLE I. ERROR OF VALIDATION DATA

Distance	Error(K=3)	Error(k=5)	Error(k=7)
Correlation	15	17.5	20
Euclidean	26.25	33.75	28.75
Cityblock	18.75	21.2500	15
Cosine	16.25	18.75	22.5

b. Neural networks

The main reason for the wide usages of neural networks for pattern recognition is the high ability of that which can model the complicated functions and it is easy to use. We use multilayer perceptron with one input layer, one hidden layer and one output layer.

The input layer is include 16 neuron in which is the number of features. The output layer has 20 neuron because of 20 kind of signature which means 20 person.

In a multi-layer perceptron with a hidden layer, when deciding is on the training features, the problem is converting to deciding on the number of units in the middle layer. Here the number of hidden layer may be at least two and a maximum of 64(almost 3times the number of input neurons). Therefore, due to the limited mode, the network performance of each of these mode have been studied using the results shown in Figure4. As can be seen, the best network performance is shown in Figure5,the overall scheme, the number of neuronsis19with a value of0.0067. Excitation functions of the middle layer and output layer of Hyperbolic tangent line is selected. Three methods for network training has been investigated 1- Back propagation 2- Conjugate Gradient Descentand3- Levenberg-Marquardt.the results inTable2shows that the best performance with the least number of iterations is for Levenberg-Marquardt method.

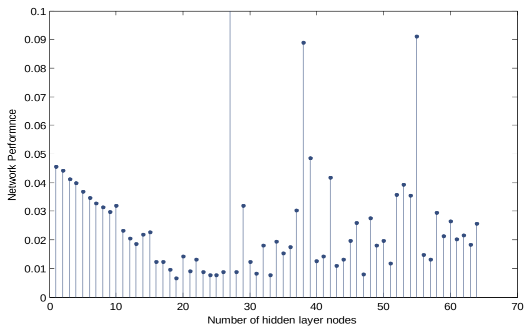

Figure 3. correlation between performance of N.N and number of neurons in the middle layer

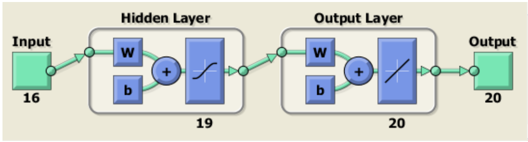

Figure 4. multilayer neural network with 1 hidden layer and 19 neuron.

TABLE II. PERFORMANCE OF THE NETWORK WITH THREE LEARNING ALGORITHM

Learning algorithm	Iterations number	Timing (second)	Network performance
Back Propagation	118	54	0.0230
Conjugate Gradient Descent	93	3	0.0196
Levenberg-Marquardt	14	7	0.0105

c. Support vector machine(SVM)

The main advantages of SVM when used for image classification problems are: (1) ability to work with high-dimensional data and (2) high generalization performance without the need to add a-priori knowledge, even when the dimension of the input space is very high. The problem that SVMs try to solve is to find an optimal hyper plane that correctly classifies data points by separating the points of two classes as much as possible. The function of this hyper plane is:

$$\mathrm{X.W + C = 0} \qquad (5)$$

where x is the point that is being validated, w is the weights, and b is the biase value.

For all n training data we have:

$$y_{\mathrm{i}}(\mathrm{x_i.w_i + b}) \geq 1 \quad \mathrm{for\ i = 1,2,\ldots,n} \qquad (6)$$

The problem is solved by maximizing the margin m, subject to the conditions imposed:

$$M = \frac{w.(x^{+} - x^{-})}{||w||} = \frac{2}{||w||} \qquad (7)$$

Input data can be extracted as features for signature, in such a way that it not be separated linearly. in this situation we can transform x to a space with higher dimension. This is called kernel function:

$$K(x, x') = \varphi(x).\varphi(x') \ (8)$$

Where ϕ (x) is transformation function

Gaussian kernel is defines as followas a kernel function:

$$K(x_i, x_j) = \exp\left(\frac{-|x_i - x_j|^2}{\sigma^2}\right) = \exp(-\gamma|x_i - x_j|^2)(9)$$

It is proved that a linear kernel, RBF kernel with parameter C is a special case for the values of C and γ. The reason for using a non-linear RBF kernel is having less number of parameters (C, γ) of the kernel compared with other nonlinear kernels that reduces the complexity of the model during the validation. To obtain optimal values for the parameters of RBF kernel package we use lib SVM. For this purpose, feature vectors have been normalized between 0 and 1, it reduces the computational complexity. Then, by using the training data, the optimal values of C and γ measured simultaneously and the results are shown in Figure 5. The values obtained for C and γ, are 32 and 0.0078125 and they are properly obtained 95%.

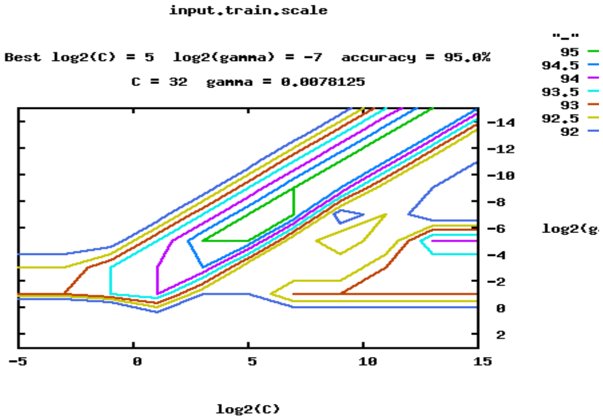

Figure 5. The obtained optimal values for C and γ for RBF kernel

III. EXPERIMENTAL RESULTS

We use 8 signatures of each person and totally 160 signatures. Table.3 shows the result of test data classification with three kind of classifiers: 1- K nearest-neighbors with K=3 and distance factor of Correlation, 2- neural network with learning method of Levenberg-Marquardt and 19 neuron in hidden layer, and 3- SVM with C=32 and γ=0.078125 .

As this table the maximum error rate is for K nearest-neighbors method and the minimum error rate is for SVM method with error rate of 4.375%.

TABLE III. PERFORMANCE OF 3-CLASSIFIER: NEAREST NEIBOR, N.N AND SVM

Classifier	True Classification Ratio(%)
K-Nearest Neighbor	79.375
Neural Network	91.25
Support Vector Machine	95.625

We have found some references in the literature that can be compared with our work.(Hairong et al., 2005) have reported 94.8% correct classification rate using SVM and the authors use 25 original signatures for each user. The number of signers is similar to our signers number but the result of our work is better.(Martinez et al.,2006)have reported 66.5% correct classification rate using SVM and 45.2% correct classification rate using Neural Network. The number of users of these authors is 38. (Özgündüz et al.,2008) have reported 75% correct classification rate using neural network and 95% correct classification rate using SVM. The user numbers of this authors is 70. In addition to the high efficiency of our method, the classifiers we use are simpler and the signatures we use for training are not a lot so the classifier can work faster and this method can be used in realistic applications. The features we use are adequate so that our approach is much more simple and efficient based on the classifiers we use like SVM.

Table.4 shows these papers results and compare them with our results.

TABLE IV. OTHER PAPERS RESULTS

Method	Classifier	Classification rate(%)
Hairong et al.[10]	SVM	94.8
Martinez et al.[12]	Neural Network	45.2
Martinez et al.[12]	SVM	66.5
Özgündüz et al.[4]	Neural Network	75
Özgündüz et al.[4]	SVM	95

IV. CONCLUSION

In this paper we present a system for signature recognition with three classifiers: nearest neighbors, neural network and SVM and we approve the results of 91.25% with N.N and 95.625% with SVM. In our method we present a new offline system based on individual preprocessing which make signatures standard and ready for feature extraction and three groups of features: global features, texture features and mask features which are completely covers all aspects of signatures and a proper classifier.According to the low amount of features this result is very acceptable and it means the preprocessing stage was suitable , the extracted features are so useful and the optimal parameters are chosen for classifiers.The recognition results of this paper prove that the method we use, combined with SVM classifier can result well .

REFERENCES

[1]-M. H. Sigari and M. R. Pourshahabi & H. R. Pourreza, “ Offline Handwritten Signature Identification and Verification Using Multi-Resolution Gabor Wavelet”, International Journal of Biometrics and Bioinformatics (IJBB), Volume (5) , Issue (4) , 2011.

[2]- A. Herdağdelen, E. Alpaydın, “Dynamic Alignment Distance Based Online Signature Verification”, The 13th Turkish Symposium on Artificial Intelligence & Artificial Neural Networks, 10-11 June 2004, Izmir, Turkey.

[3]-M.S.Arya and V.S.InamdarA, “Preliminary Study on Various Off-line Hand Written Signature Verification Approaches”, International

Journal of Computer Applications (0975 – 8887),Volume 1 , No. 9, 2010.

[4]- E. Özgündüz,T,Şentürk and M. Elif Karslıgil, "OFF-Line Signature Verification and Recognition by Support Vector Machine",Document Analysis and RecognitionI,NinthInternational Conference on,Volume 2,pages 734-738,23-26 Sep 2008.

[5] Manoj Kumar, "Signature Verification Using Neural Network", International Journal on Computer Science and Engineering (IJCSE),1498-1504,Sep 2012.

[6] H. Baltzakis- N. Papamarkos, "A new signature verifcation technique based on a two-stage neural network classifier", Engineering Applications of Arti®cial Intelligence14, 95-103,2001.

[7] Mrs. Tulsi Gupta,"Off-line Signature Verification", International Journal of Computer Application Issue 2, Volume 3 ,June 2012.

[8] Emre Özgündüz,Tülin Şentürk and M. Elif Karslıgil," Off-Line Signature Verification and Recognition by Support Vector Machine", In 13th European Signal Processing Conference ,Sep 2005 .

[9] I . A. Ismail, M . A. Ramadan, T. El danf, A. H. Samak,"Automatic Signature Recognition And Verification Using Principal Components Analysis", Fifth International Conference on Computer Graphics, Imaging and Visualization,Pages 356-361,2008.

[10] Hairong Lv, Wenyuan Wang, Chong Wang, Qing Zhuo ,"Off-line Chinese signature verification based on support vector machines", Pattern Recognition Letters 26 ,2390–2399,2005.

[11]- Alan McCabe, Jarrod Trevathan and Wayne ReadNeural, " Network-based Handwritten Signature Verification", Journal of Computers, Vol. 3, No. 8, August 2008.

[12]- E.F.Martinez, A.Sanchez and J.Velez, "Support Vector Machines versus Multi-Layer Perceptrons for Efficient Off-Line Signature Recognition",Engineering Applications of Artificial Intelligence,Volume 19, Issue 6, Pages 693–704, Sep 2006.