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Persian off-line signature recognition with structural and rotation invariant features using by one-against-all SVM classifier

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Abstract

The problem of automatic signature recognition has received little attention in comparison with the problem of signature verification, despite its potential applications for many business processes and can be used effectively in paperless office projects. This paper presents model-based off-line signature recognition with rotation invariant features. Non-linear rotation of signature patterns is one of the major difficulties to be solved in this problem. The proposed system is designed based on support vector machines (SVM) classifier technique and rotation invariant structure feature to tackle the problem. Our designed system consists of three stages: the first is preprocessing stage, the second is feature extraction stage and the last is SVM classifier stage. Experimental results demonstrated that the proposed methods were effective to improve recognition accuracy.

Keywords: *Persian off-line signature recognition; Rotation invariant; structural feature; SVM*

1. Introduction

The signature recognition is used as a popular, cost effective authentication method and preferred among various biometrics as it is the widely accepted way to identify an individual. Signature recognition is not only a major area of research in the field of image processing and pattern recognition, but also widely used in many areas of society, related to automated banking transaction, electronic fund transfers, document analysis, access control, contractual matters and security throughout the world. Signature recognition is an important form of Biometric identification and probably one of the oldest biometric recognition methods.

Signature is a special case of the hand written note which results in a complex process of writing a series, based on the motion curve muscle movements, associated with the idea of signing, which includes special characters with special art of writing.

There is a growing interest in the area of signature recognition and verification. The purpose of the signature recognition process is to identify the writer of a given sample, while the purpose of the signature verification process is to confirm or reject the sample. There are two major categories: on-line and off-line. In the on-line systems, data are obtained using special peripheral device, while in the off-line systems, images on the signature which are written on a paper are obtained using scanner.

Although some people believe that the signature recognition is unreliable in comparison with the other methods, signature is still used to recognize so many people in many cases. This method is also cost-effective and accepted by societies. Getting a finger print may be considered as an offensive matter to a person while getting a signature is never offensive. An important advantage of signature is the recognition in absentia and it is the concept that all people in many cultures, languages and nationalities are known.

In this research, an approach for off-line signature recognition is proposed. The designed system consists of three stages: the first stage is pre-processing stage which applied some operations and filters to improve and enhance the signature image. That image is ready for the next stage which is the feature extraction stage. Choosing the right feature is an art more than a science. Three powerful features are used boundary, geometric and global features. The last stage is the Support vector machine classifier. The simulated results indicate that the proposed method has a high accuracy in Persian signature recognition.

This paper is organized as follows: Section II related work, Section III preprocessing, Section IV feature extraction, Section V support vector machine, Section VI Proposed method , Section VII experimental result and Section VIII Conclusion the paper and shows scope of future work.

2. Related work

Signature recognition systems are different in two main sections which are feature extraction and decision processing. Some of the errors occur in the pattern recognition are: False Rejection and False Acceptance. False Rejection typically is the legitimate user rejected because the system does not find the user's current biometric data similar enough to the master template stored in the database and False Acceptance the state which an imposer accepted as a legitimate user because the system finds the imposter's biometric data similar enough to master template of a legitimate user[1].

Many studies have been done on the signature recognition. This section is a short overview of a number of methods.

Frias-Martinez et al. [2] have presented a signature recognition method base on SVM and compared with the similar method based on MLP. Two experiments have been done in this research in which one feature type has been used. One was done according to the global feature and the vertical and horizontal projections of a signature image and the other has used the simple image as a feature. To examine the system, it was tried to consider the property of a real signature recognition system. So, only one signature of each individual was used for system training. The gained accuracy for signature recognition is 66.5% by using SVM while the simple image was given to it as input where as it is 71.2% for the global features input. This is while the MLP has gained 45.2% of accuracy by inputting the simple signature image with 46.8% of accuracy and global features input.

Ismail et al. [3] proposed an off-line Arabic signature recognition and verification technique. In their paper, a system of two separate phases for signature recognition and verification is developed. The recognition phase, some features based on Translation, circularity feature, image enhancement, partial histogram, centers of gravity, global baseline, thinning etc. are extracted. A set of signature data, consisting of 220 genuine samples and 110 forged samples is used for experimentation. They obtained a 95.0% recognition rate.

Özgündüz et al. [4] have also presented a signature recognition and verification system by using SVM. Binarization, noise reduction, width normalization and skeletonization have been done as preprocessing section. Then, global, oriented and grid features have been extracted. The global features include area, width and length ratio, vertical and horizontal central gravity, etc. Oriented features calculate the signature line gradient. The signature image is divided to 60 equal parts and the signature area is gained in each one. SVM classifier has been used to recognize and verify signature. The signature recognition error has been reported 5%.

Kaewkongka, Chamnongthai and Thipakom [5] proposed a method of off-line signature recognition by using Hough transform to detect stroke lines from signature image. The Hough Transform was used to extract the parameterized Hough space from signature skeleton as unique characteristic feature of signatures. In the experiment, the Back Propagation trained Neural Network was used as a tool to evaluate the performance of the proposed method. The system was tested by 70 test signatures from different persons. The experimental results reveal the recognition rate 95.24%.

Radmehr, Anisheh and Yousefian [6] proposed a new offline signature recognition is presented. In the first step, radon transform is initially applied on the signature image with 0°, 45°, 90° and 135° angles. Then fractal dimension of the obtained vectors is calculated and the results are fed into SVM classifier. The simulated results indicate that the proposed method has a high accuracy in signature recognition.

3. Preprocessing

The signature images require some manipulation before the application of any recognition technique. Signatures are scanned in a colored image. In this phase, signatures are made standard and ready for feature extraction. The preprocessing stage follows seven steps: Grayscale, Noise reduction, Binarization, Image cropping, skeletonization, rotation normalization and width normalization.

The signature image is converted to grayscale and then binarized using a histogram-based binarization [7]. The binary image of the signature contains only 0's and 1's. Impulse noise is caused by malfunctioning pixels in Scanner, faulty memory locations in hardware or transmission in a noisy channel. Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. Therefore, at this stage, we apply the algorithms on the image to reduce the noisy pixels [8]. While collecting signature samples, it was observed that users gave consecutive samples having angular variations approximately from –60° to +60°. Hence, before feature extraction, to perform rotation normalization, the signature curve was rotated until the axis of least inertia coincided with the horizontal axis [9].

To do this purpose, the following Algorithm is used, signature curve as:

$$C = \{(x_i, y_i), i = 1, \dots, N\} \tag{1}$$

N being the number of black pixels of the signature, and $(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)$ the coordinates of each one of those pixels, the axis of least inertia describes the trend of the signature pixel set. The corresponding parameters, horizontal $(\bar{x})$ and vertical $(\bar{y})$ centers of gravity and the second order moments $\overline{x^2}$ and $\overline{y^2}$ of a signature are computed as

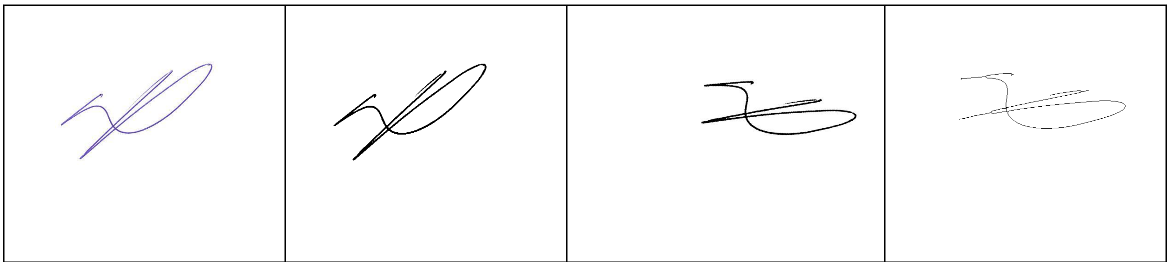
$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2}$$

$$\overline{x^2} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \qquad \overline{y^2} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2 \tag{3}$$

The orientation of the axis of least inertia was then given by the orientation of the least Eigen vector of the matrix in Eq. (4).

$$I = \begin{pmatrix} \overline{x^2} & \bar{x}\bar{y} \\ \bar{x}\bar{y} & \overline{y^2} \end{pmatrix} \tag{4}$$

Once, this angle was obtained, all the points in the signature curve under consideration were rotated with this angle. Usually the scanning image for any signature may consist of the area of the signature and its surrounding. Thus the image may include an additional empty lines and columns that have no data (space lines). These empty lines should be eliminated by tracing from outside margins towards inside and stopped at the first occurrence of on-pixel at each side of the four edges[10]. Thus, the white space surrounding the signature is discarded. The cropped image is scaled using bicubic interpolation to a constant width, keeping the aspect ratio fixed. The skeletonization algorithm[11] proposed by is used in order to reduce data storage without losing the structural information of the image as well as to facilitate the extraction of morphological features from digitized patterns. A typical scanned and Preprocessed Signature is shown in Figure 1.



A. Master Image	B. Binary Image	C. Rotation Normalization Image	D. skeletonization Image

Figure1: Preprocessing Signature Image

4. Feature extraction

Feature extraction process is an important step in deploying any signature recognition systems since it is the key to identify and differentiate a user's signature from another. Features are classified into two main groups: Global & Local features. Global features are extracted from a whole signature, based on all sample points in the input signature and local features which represent a portion or a limited region of the signature[3]. In this paper, we are using various feature extraction algorithms. The feature set includes the three methods i.e. Boundary feature, novel geometric feature and global rotation invariant feature.

4.1 Boundary features

The boundary (μ) of signature consists of a finite number of an ordered sequence of points (λ) that define the shape of the signature, see Figure1; $\mu = \{\lambda_i = (x_i, y_i), \quad i =$

$0, \ldots, N-1\}$ several assumptions are made about μ: closed, a single point thickness, traversed in a counter-clockwise sense and does not contain any internal holes[12].

We extract four types of features from a signature's boundary:

A. The boundary inter-distance: This represents the distance (d_{ij}) between a pair of points, λ_j and λ_i, on μ and is given by, $d_{ij} = d(\lambda_i, \lambda_j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$ where λ_i, λ_j have coordinates $(x_i, y_i), (x_j, y_j)$ respectively.

B. Chord bending: Chord bending (λ) represents the amount of parameter bending between a pair of points on μ. For any pair of points, $\lambda_i, \lambda_j \in \mu$, the chord bending is defined as the ratio of the distance function between the pair of points (d_{ij}) to the parametric distance between the pair of points (p_{ij}), $\gamma_{ij} = \frac{d_{ij}}{\min(p_{ij}^{+}, p_{ij}^{-})}$ where p_{ij}^{+} is counter-clockwise direction and the other p_{ij}^{-} the clockwise direction.

C. Local curvature: The local curvature (K_i°), represents the amount of local boundary bending by computing the local angle of the tangent, $K_i^{\circ} = \cos^{-1}(\hat{V}_{i-1} . (-\hat{V}_i)). sign(\hat{V}_{i-1} * \hat{V}_i)$,

where $\hat{V}_i = {V_i}/{|V_i|}$ and $V_i = (x_{i+1} - x_i)\hat{\imath} + (y_{i+1} - y_i)\hat{\jmath}$.

D. Relative orientation: The relative orientation (x_{ij}) of a point γ_j with respect to γ_i , is given by

$\alpha(\gamma_i \gamma_j) = \arctan(y_j - y_i, x_j - x_i)$

4.2 Geometric features

The proposed method used geometric center for feature extraction. This feature is well suitable for classifier and fast in computation. Here, feature points are nothing but geometric centers. The procedure for finding feature points by vertical and horizontal splitting is mentioned in Algorithm based on the least square line [13]. This line describes the trend of the signature pixel set. The least-square line is defined by the parameters b and m as: $y = mx + b$

The corresponding parameters b and m are computed as:

$$b = \frac{(\sum_{i=1}^{N} x_i^2)(\sum_{i=1}^{N} y_i) - (\sum_{i=1}^{N} x_i)(\sum_{i=1}^{N} x_i y_i)}{N(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)^2} \qquad m = \frac{N(\sum_{i=1}^{N} x_i y_i) - (\sum_{i=1}^{N} x_i)(\sum_{i=1}^{N} y_i)}{N(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)^2}$$

N: black pixels of signature image,$(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$

Six feature points are retrieving based on horizontal splitting. This is the procedure for generating feature points based on horizontal splitting.

1. Split image with horizontal line, (The line is parallel with least square line at the center of gravity).
2. Find geometric centers h_1 and h_2 for top and bottom parts correspondingly.
3. Split top part with vertical line at h_1 and find out geometric centers h_3, h_4.
4. Split bottom part with vertical line at h_2 and find out geometric centers h_5, h_6.

Six feature points $(v_1, v_2, v_3, v_4, v_5, v_6)$ are retrieving based on vertical splitting.

4.3 Global features

It is important to extract appropriate feature sets to represent signature for match evaluation. Moreover, obtained signatures always show different orientations of various rotation angles. This motivates us to design the following circular global feature to deal with the rotation problem. The important property of circular global feature is that they are able to detect interpersonal change by circular projection, and they are periodical to make the resulting feature vectors for the same writer identical with only phase shift in fact.

We suppose that each of the two-dimensional signature patterns is denoted by $f(x, y)$. Thus, we may find the center of gravity from the signature image at first, which is given by $\mathbf{C_v} = \frac{\sum_i i*P_h[i]}{\sum_i P_h[i]}$, $\mathbf{C_h} = \frac{\sum_i i*P_v[i]}{\sum_i P_v[i]}$ where P_h *and* P_v are horizontal and vertical projection.

Next, an enclosing circle whose center locates at gravity point with $R = \max_i \sqrt{(x_i - C_v)^2 + (y_i - C_h)^2}$ is determined. Where (x_i, y_i)stands for a black pixel in the signature image. Thus the signature can be completed enclosed in the circle.

Further, we convert Cartesian coordinate into the polar coordinate based on $x = r\cos\theta$, $y = r\sin\theta$ relations. Assume that we divide the signature image in the circle into 360 equal sectors, along the enclosing circle of the signature, at equally spaced intervals and in a revolving fashion. The RPF calculates the numbers of white pixel in each signature partition.

There are two types of such extraction [14]: ring-external-feature (REF) and ring-internal-feature (RIF). REF is the ring projection area between the virtual circle frame and white-to-black pixel jump toward the center of circle, it is well suitable for describing the whole signature external shape. The RIF calculates the ring projection area between the first white pixel and the first white-to-black pixel jump beginning from the center of circle. Consequently, it may represent more internal detail structure features such as stroke relative positions, etc.

5. Support vector machine

Classification is the last step of signature recognition. Support Vector Machines (SVM) is originally designed for binary classification. Vapnik [15] introduced the concept of SVM in the late 1970's. The basic idea of SVM is deceptively simple. Given a set of vectors in $\mathrm{R_n}$, labeled positive or negative that is separable by a hyper plane, SVM finds the hyper plane with the maximal margin. In this mode, the kernel of SVM classifier is a one order polynomial classifier. Sometimes, more complicated kernels such as higher order polynomial, MLP and Radial Basis Functions (RBF) are used. To evaluate performances of our approach, we use the SVM classifier with a radial basis function (RBF kernel). Results are obtained, using the cross-validation approach involving training, validation and testing steps [16].

Essentially, SVM is a binary classifier, i.e. SVM can categorize two classes. Therefore, for classification of N classes, N SVM classifiers are needed. For signature recognition, number of SVM classifiers is equal with number of signers. The conventional way to extend it to multiclass scenario is to decompose an N-class problem into a series of two-class problems, for which one-against-all is the earliest and one of the most widely used implementations [17].

It constructs K SVM models where K is the number of classes. The i th SVM is trained with all of the examples in the ith class with positive labels, and all other examples with negative labels. Thus given l training data $(x_1, y_1), \ldots, (x_l, y_l)$, where $x_i \in R_n$,$i = 1, \ldots, l$ and $y_i \in \{1, \ldots, k\}$ is the class of x_i,the ith SVM solves the following problem:

$$\min_{\omega^i, b^i, \varepsilon^i} \quad \frac{1}{2}\left(\omega^i\right)^T \omega^i + C\sum_{j=1}^{l} \varepsilon_j^i \left(\omega^i\right)^T$$

$$(\omega^i)^T \emptyset\left(x_j\right) + b^i \geq 1 - \varepsilon_j^i\,, \qquad if\ \ y_j = i$$

$$(\omega^i)^T \emptyset\left(x_j\right) + b^i \leq -1 + \varepsilon_j^i\,, \qquad if\ \ y_j \neq i$$

$$\varepsilon_j^i \geq 0\,, \quad j = 1, \dots, l$$

Where the training data x_i are mapped to a higher dimensional space by the function $\emptyset$ and C is the penalty parameter. Minimizing ${}^1\!/_2 \left(\omega^i\right)^T \omega^i$ means that we would like to maximize $2/\|\omega_i\|$, the margin between two groups of data. When data are not linear separable, there is a penalty term $C\sum_{j=1}^{l}\varepsilon_j^i$ which can reduce the number of training errors. The basic concept behind SVM is to search for a balance between the regularization term ${}^1\!/_2 \left(\omega^i\right)^T \omega^i$ and the training errors.

After solving, there are k decision functions $(\omega^1)^T \emptyset(x) + b^1$ ... $(\omega^k)^T \emptyset(x) + b^k$, We say x is in the class which has the largest value of the decision function class of $x \equiv \arg\ \max_{i=1,\dots,k}(\,(\omega^i)^T \emptyset(x) + b^i$

This manner a SVM classifier is used per class that classifier output is negative or positive. When all classifier outputs except only one classifier are negative, the class of input signature will be the corresponding class of classifier that generates positive. When the output of all classifiers is negative or two or more classifier outputs are positive, the input signature will not belong to any known class.

6. Proposed Method

In the available literature, the handwritten signature recognition problem has been approached in various ways. In general, handwritten recognition is a difficult task because of the variation of writing styles even with the same writer; therefore, great attentions must be taken in designing a recognition system. The current research presents satisfactory results in the recognition of handwritten signatures. The block diagram of the system is given in Figure 2.

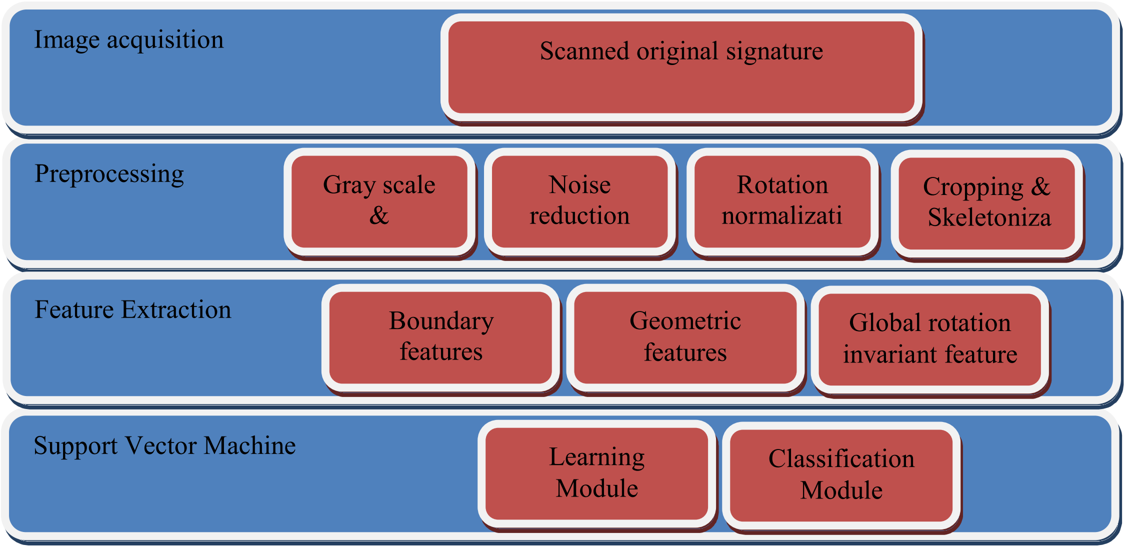


Figure2: The block diagram of proposed signature recognition system

Signature Recognition Systems need to preprocess the data. It includes a series of operations to get the results. The major steps are as follows:

6.1 Image Acquisition

The signatures to be processed by the system should be in the digital image format. We need to scan the signatures from the document for the recognition purpose.

6.2 Signature Preprocessing

We have to grayscale and binarization the signature, remove the background noise, rotation normalization, resize it to proper dimensions, cropping and thin the signature. This yields a signature template which can be used for extracting the features.

6.3 Feature Extraction

We are using various feature extraction algorithms. The feature set includes the conventional global rotation invariants features of signature as well as new features. The new features that are proposed include the boundary inter-distance, chord bending, local curvature, relative orientation and Successive Geometric centers.

6.4 Support Vector Machine

The system we introduce is in two major parts: training signatures and recognition of given signature. The extracted features are stored in to database. The human signature is dependent on varying factors, the signature characteristics change with the psychological or mental condition of a person, physical and practical condition like tip of the pen used for signature, signatures taken at different times, aging etc. We train the system using a training set of signature obtained from a person. Designing of a classifier is a separate area of research. The decision thresholds required for the classification are calculated by considering the variation of features among the training set. Separate set of thresholds (user Specific) is calculated for each person enrolled, some system also use common threshold form all users. The performance of system depends on how accurately the system can recognize the signatures.

7. Experimental result

The signature database images which the experiment worked on were taken from employees and some engineering university students of sari Azad Islamic university. Employees database include 20 different classes in which 5 signatures existed and also 20 different classes in which 12 classes of signature are in university students database. All the signatures have been taken by black pens on a white sheet in different times. The presented algorithm has also been implemented by MATLAB software.

The presented SVM method is a binary classifier. The binary classifier combination should be used for M class matters. To do this purpose, one Against the all or one Against one-pair wise or hierarchical methods can be used[17]. One against the all method was used in this research. 40 classifiers are made which each of them separates one signature from the others. To get the answer, the target sample is given to each of those classifiers. The classifier which produces the biggest output amount will determine the input sample class.

Table.1: the percentage of recognition in the research algorithm applying on different data

	Signature databases	Recognition percents
1	Employees	92%
2	Students university	94.4%
3	Componential samples	92.8%

8. Conclusion

As mentioned, signature is one of the most practical tools in official and business works which its recognition is an important matter by computers. Structural features and SVM classifier were used for signature recognition which is acceptable. Using fuzzy shape curves to extract the signature structural features and colonial selection or genetic algorithm in classifier section of artificial immune system are suggested as the future task.

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