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Writer-independent Offline Signature Recognition based upon Fourier Descriptors

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ABSTRACT
Signatures of individuals play an important role in financial, commercial and legal transactions and hence require a secured recognition and verification system. This paper presents a novel approach towards signature recognition using Fourier Descriptors. The signature image is enclosed in a closed contour and the Fourier terms of these contours are computed by representing the contour in a complex plane. The FDs computed are then fed to K-NN classifier for recognition. The proposed system exhibits good recognition accuracy.

Keywords
Fourier Descriptors, recognition, signature, biometric.

1. INTRODUCTION
Biometrics [1] covers a variety of technologies in which unique identifiable attributes of people are used for identification and authentication. These include a person's fingerprint, iris print, hand, face, voice, gait or signature, which can be used to validate the identity of individuals seeking to control access to computers, airlines, databases and other areas which may need to be restricted. In this paper we focus on signature identification.

There are two key types of digital handwritten signature authentication, Static and Dynamic [2]. Static is most often a visual comparison between one scanned signature and another scanned signature, or a scanned signature against an ink signature. In dynamic digital handwritten signature authentication data is captured digitally usually using digitized pen and graphical tablets.

Signature recognition and verification involves two separate but strongly related tasks: one is the identification of the signature owner, and the other is the decision about whether the signature is genuine or forged. Static signature verification relies on image processing and feature extraction techniques. In general, the signature verification system comprises of two parts: one, template creation by capturing the genuine signatures of each individuals of interest to application under study. The second, verification of the given input signature as genuine or forgery (false signatures of an individual). The second part involves two sub stages:

Identification- Checking for a person’s identity along with the whole database of signatures prepared in part one. Basically we compare the input signature image for each subject with whole of the database i.e. with samples from all subjects in the database.

Verification- Verification is the process of comparing input signature image with samples from the same subject only. This process basically deals with person’s identity verification.

In either part, the input signature image has to undergo pre-processing steps for making the image ready for extraction of features of interest, either for template creation and/or for authenticating the signature.

Three types of forgeries are identified in the literature:

1) Random Forgery: An individual creates a signature just by knowing the name of the person in the signature.
2) Unskilled Forgery: The signer creates a signature after observing the signature without any prior experience.
3) Skilled Forgery: The signer, a professional, replicates a signature after observing the signature carefully and practicing the original signature prior to creating the signature.

In any case, the system should be able to detect the forgery. The task of forgery detection in case of skilled forgery is challenging since, there will be lot of similarity among the signatures compared to other type of forgeries. It is difficult to distinguish between genuine and skilled forgery visually unless a deep insight is gained looking into various geometrical aspects of the genuine signature. Sample images of forgery are shown in figure 1.

(a) (b) (c) (d)

Figure 1. Sample signatures (a) genuine (b) skilled forgery (c) unskilled forgery (d) random forgery

Writer independent automatic signature verification systems are either off-line or online. In either case, a classifier, in general, supervised classifier, applied to signature verification is trained using training samples collected from a complex underlying distribution. The classifier is trained from a sufficient set of previously collected genuine signatures, wherein these dataset signatures are representative of the entire population of legitimate users enrolled to the verification system.

Several feature extraction techniques have been proposed in the literature for signature verification [3]. Studies have suggested the use of single feature as well as multiple features for the biometric recognition systems [4, 5, 6, 7].In this paper, we propose an efficient approach for recognition of the signature as belonging to specific person. The approach comprises of enclosing a closed boundary over the entire signature image and computing Fourier descriptors of the boundary as features representing the signature image. These features are input to K-NN classifiers to recognize the signature as belonging to specific person by comparing the input features with that of the features available in the database. The authentication of the same is the future work we are going to propose later. The rest of the paper is described as below. The pre-processing steps are described in the section 2. Section 3 presents the feature extraction method and section 4 describes the recognition process. Experimental results are discussed in section 5 and conclusions are presented in section 6.

2. PRE-PROCESSING

Pre-processing includes operations like noise removal, binarization, rotation normalization, resizing, and thinning. The acquired signature, in gray scale, usually through a scanning device, may contain extra dots which are unwanted. These extra dots (salt and pepper noise) can be removed by usage of median filters on the captured signature image. The required time to process gray/colored image is longer than binary one. Hence, the signature image is binarized (black and white pixels) using a thresholding based technique. Otsu's method is preferred for binarization [8]. Rotation of a signature is necessary to minimize the impact of angular variations introduced over time. It aligns the axis of mass of inertia of all the signatures to the same horizontal axis. In one approach for achieving the alignment, the edge of the signature is detected using an edge detector and thinned (or skeletonized) to which Radon transform is then applied and the angle of rotation is measured in anticlockwise direction. The signature is then rotated clockwise to remove skewness.

Comparing of signatures having the same shape but of different sizes would lead to low similarity scores. Size normalization is therefore applied to remove that affect. All the signatures having same normalized size makes our task easy to compare reference (created in first part) and test (classification of input signature image as genuine or forgery) samples. To achieve size normalization, a bounding box is fitted on the signature so as to remove the background and then the signature is cropped out. There is no general agreement in the size of the normalized image. The size varies from 40 x 40 pixels to rectangular size 200 x 300 pixels, arbitrarily selected by the researchers in their research work. However, the aspect ratio (width and height of the signature) is taken care during size normalization.

The resized image is thinned to get a single pixel run of the image of signature. Even though it is not a pre-requisite, the operation enables us to retain only most essential details of the signature. Further, this operation, in general, reduces the load on feature extraction module by discarding the unnecessary pixels in the signature image. The results of pre-processing steps are presented in figure 2.

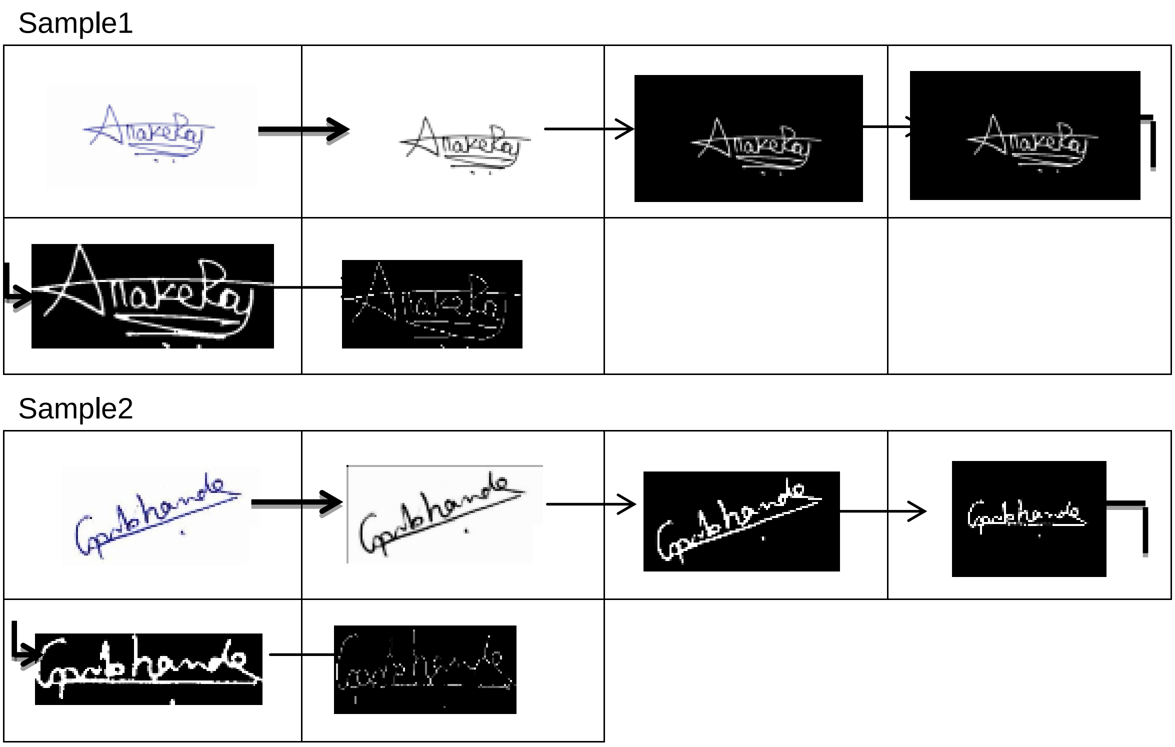

Figure2. Pre-processing of offline signature images

3. FEATURE EXTRACTION

Fourier Descriptors (FDs) are widely used in shape analysis [9, 10, 11]. The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shape of the object in a frequency domain. First, the N points forming the boundary of a region are required by taking all the pixels occupied by the boundary, or taking N samples from the boundary. This can be done by tracing the boundary counter clockwise. The region can be viewed as being in the complex plane with the ordinate being the imaginary axis and the abscissa being the real axis as depicted in Fig. 3. The xy coordinates of each point in the shape contour can be expressed in the form of (x_k,y_k) where $0 < k \le N-1$. A complete set of coordinates describing the boundary is determined. The contour can then be expressed as coordinate series s(k) = [x(k), y(k)], for k = 0,1, 2,…….,N-1 where s(k) = x(k) + j y(k). The Discrete Fourier Transform (DFT) of this sequence is the FD of the contour [12]. The DFT of s(k) is:

$$F(u) = \frac{1}{N}\sum_{k=0}^{N-1} s(k)e^{\frac{-j2\pi k u}{N}} \quad \text{for } k = 0,1,2,\ldots,N-1$$

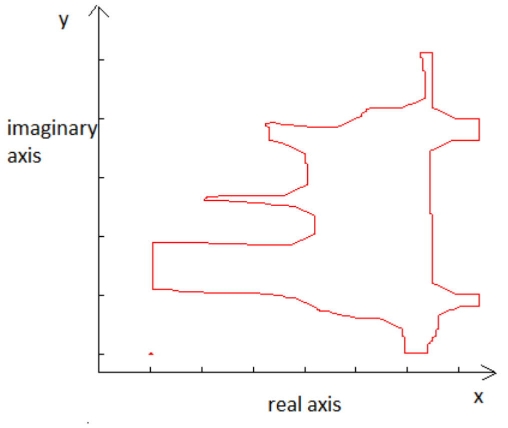

Figure 3. Contour of the signature represented in complex plane

The normalized magnitude of the FD can eliminate dependency on shape size. The high frequency descriptors contain information about finer details of the shape while the low frequency descriptors contain information about the general or global features of the shape. The optimal number of FD to be selected for shape recognition has to be determined since the number of terms is too large.

To adopt FD, a boundary tracing need to be performed on the signature image. The optimal number of FD required for signature shape recognition is determined empirically. Since, a signature may comprise of more than one component, in general, we enclose the entire signature in a closed curve that fits the signature. Morphological operations are used to achieve the enclosing closed curve. The curve so obtained is different for different signatures and hence can be used effectively to compute FDs for shape recognition. Sample contour images are depicted in Figure 4. The invariant Fourier descriptors are computed as defined in our earlier work for character recognition [13].

4. RECOGNITION

K-NN classifier has been chosen to evaluate the effectiveness of FD as feature vectors for recognition of signature images. The recognition is made comparing the array of templates of the signature (in terms of its FDs) to be recognized with all the arrays of the other signatures (in terms of its FDs) of the database using K-NN classifier: the signature is correctly classified to a specific signature of the database based on the minimum distance achieved. The distance computation is carried out using Euclidean distance measure. The K-nearest neighbors are computed as described below.

1. Determine the number of nearest neighbours i.e. value of K. Generally K is chosen to be odd integer vale i.e. 1,3,5,…
2. Calculate the distance between query instance and all the training samples. Distance computation can be done using a distance criterion such as Euclidean distance.
3. Sort the distance and determine the nearest neighbours based on the kth minimum distance.
4. Gather the category/label of the nearest neighbours. Normally the labels are associated with the training sets only.
5. Using the simple majority of the the category of the nearest neighbours as the prediction value (label) of the query instance

Enclosing boundary of sample signature images

Figure 4. Sample signature images and their enclosing curves

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

The objective here is to assess and compare the performance of the method proposed in this paper for signature recognition. Ten subjects were chosen at random, belonging to different professions. Signatures were collected on a white A4 paper at different point of time, to capture the variations, if any. A total of 16 signatures were collected from each subject. The signatures pages were scanned at 300 dpi, in gray scale, using a flatbed scanner and individual signatures were cropped out using horizontal and vertical profile operations. Out of 16 signatures, 10 signatures were selected for training purpose and rest of the other for testing, arbitrarily. Hence, the training set constituted of a total of 100 signatures and that for testing, 60 signatures were available. For all the training samples, FDs of 64 dimensions were computed and were labelled as belonging to specific subjects, i.e. 10 labels for 100 one dimensional vectors, each vector containing 64 dimension FDs. For each of the test samples, FDs of 64 dimensions were computed, without assigning labels. The resulting training vectors and test vectors comprising FDs as features representing the signature images were input to K-NN classifier. For each reference signature Sr, the corresponding feature vector xr extracted from the signature image is stored in the system's knowledge base during the training phase. In recognition mode, the image of a questioned signature Sq is presented to the system and its feature vector x_q, along with the reference set $\{x_r\}$ of signatures of the users enrolled to the knowledge base, are presented to K-NN module for recognition. The block diagram is presented in Figure 5.

The results are better for K=1 compared to other values of K. The wrong classification is attributed to the fact that the enclosing boundary for that signature instance differed compared to other samples in the image, aroused out of common structuring element used for filling the gaps in the pre-processed image (Fig. 6)

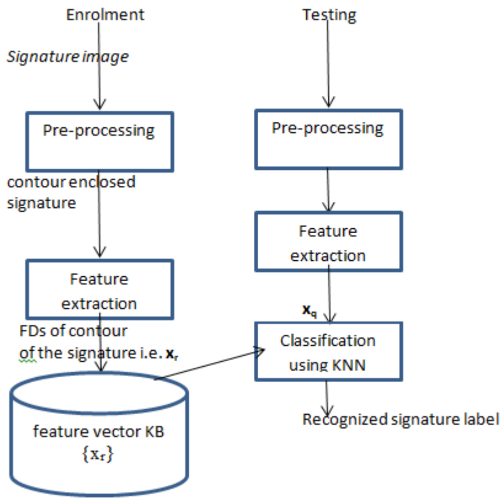

Figure 5. Block diagram of the proposed method

The results of the classifier are presented in Table 1.

Table 1: Recognition results using K-NN classifier

Subjects	No. of train/test	Recognition	
		K=1	K=3
1	10/6	6	6
2	10/6	6	6
3	10/6	4	5
4	10/6	5	6
5	10/6	4	4
6	10/6	6	2
7	10/6	3	4
8	10/6	5	5
9	10/6	6	5
10	10/6	5	4

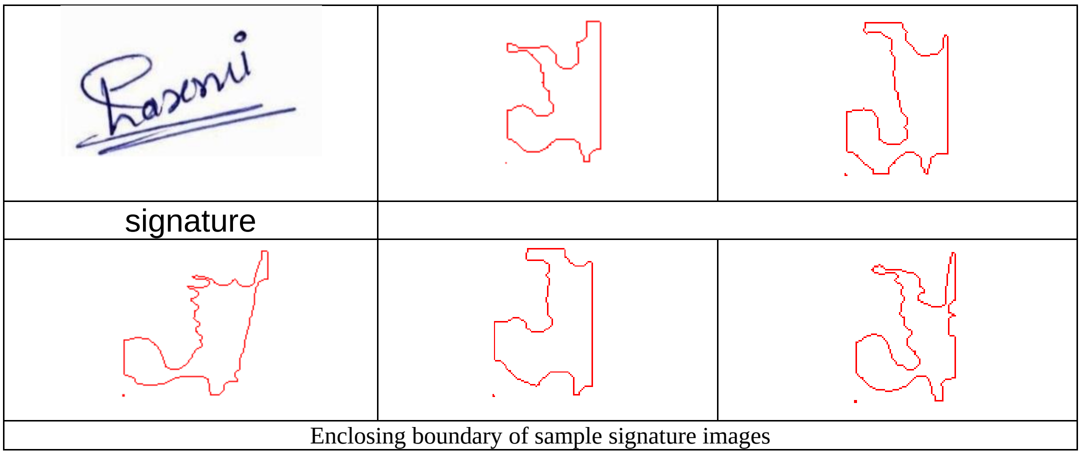

Figure 6. Sample images showing varying enclosing boundaries

6. CONCLUSION

In this paper, an efficient approach towards signature recognition has been presented. FDs are used for feature extraction and K-NN is used for recognition purpose. The results obtained show the efficacy of the proposed system. The next stage of recognition is the authentication process. However, the authentication can have a significant class overlap, especially between genuine signatures and simulated forgeries, and hence require a proper choice of threshold for accepting the recognized signature as authentic. We are working on the same by fine tuning the FDs and perform the validations in terms of parameters, namely, false acceptance rate and false rejection rate.

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