An Efficient Off-line Signature Identification Method Based On Fourier Descriptor and Chain Codes

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Summary
This paper presents a novel off-line signature identification method based on Fourier Descriptor (FDs) and Chain Codes features. Signature identification classified into two different problems: recognition and verification. In recognition process we used Principle Component Analysis. In verification process we designed a multilayer feed forward artificial neural network. The main steps of constructing a signature identification system are discussed and experiments on real data sets show that the average error rate can reach 3.8%.

Key words:
signature recognition , Fourier Descriptor , Principle Component Analysis , personal verification

1- Introduction

Handwritten signature is one of the most widely accepted personal attributes for identity verification. As a symbol of consent and authorization, especially in the prevalence of credit cards and bank cheques, handwritten signature has long been the target of fraudulence. Therefore, with the growing demand for processing of individual identification faster and more accurately, the design of an automatic signature verification system faces a real challenge.

Handwritten signature recognition can be divided into on-line (or dynamic) and off-line (or static) recognition. On-line recognition refers to a process that the signer uses a special pen called a stylus to create his or her signature, producing the pen locations, speeds and pressures, while off-line recognition just deals with signature images acquired by a scanner or a digital camera. In general, off-line signature recognition is a challenging problem. Unlike the on-line signature, where dynamic aspects of the signing action are captured directly as the handwriting trajectory, the dynamic information contained in off-line signature is highly degraded. Handwriting features, such as the handwriting order, writing-speed variation, and skillfulness, need to be recovered from the grey-level pixels.

In the last few decades, many approaches have been developed in the pattern recognition area, which approached the offline signature verification problem. Justino, and et al. (2002) propose an off-line signature verification system using Hidden Markov Model . Zhang, Fu and Yan (1998) proposed handwritten signature verification system based on Neural 'Gas' based Vector Quantization . Vélez, Sánchez and Moreno (2003) propose a robust off-line signature verification system using compression networks and positional cuttings . Arif and Vincent (2003) concerned data fusion and its methods for an off-line signature verification problem which are Dempster-Shafer evidence theory, Possibility theory and Borda count method . Chalechale and Mertins used line segment distribution of sketches for Persian signature recognition . Sansone and Vento (2000) increased performance of signature verification system by a serial three stage multi-expert system .

Inan Güler and Majid Meghdadi (2008) propose a method for the automatic handwritten signature verification (AHSV)is described. This method relies on global features that summarize different aspects of signature shape and dynamics of signature production. For designing the algorithm, they have tried to detect the signature without paying any attention to the thickness and size of it . Jing Wen,BinFang, Y.Y.Tang and TaiPing Zhang (2009) presents two models utilizing rotation invariant structure features to tackle the problem. In principle, the elaborately extracted ring-peripheral features are able to describe internal and external structure changes

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of signatures periodically. In order to evaluate match score quantitatively, discrete fast Fourier transform is employed to eliminate phase shift and verification is conducted based on a distance model. In addition, the ring-hidden Markov model (HMM) is constructed to directly evaluate similar between test signature and training samples .

In this paper we present a new off-line signature identification. Our method used Fourier Descriptor and Chain Codes as a features for represent the signature image. Identification process classified into two different problems: recognition and verification. In recognition process we used Principle Component Analysis. In verification process we designed a multilayer feed forward artificial neural network. Figure 1 present a general view about our method.

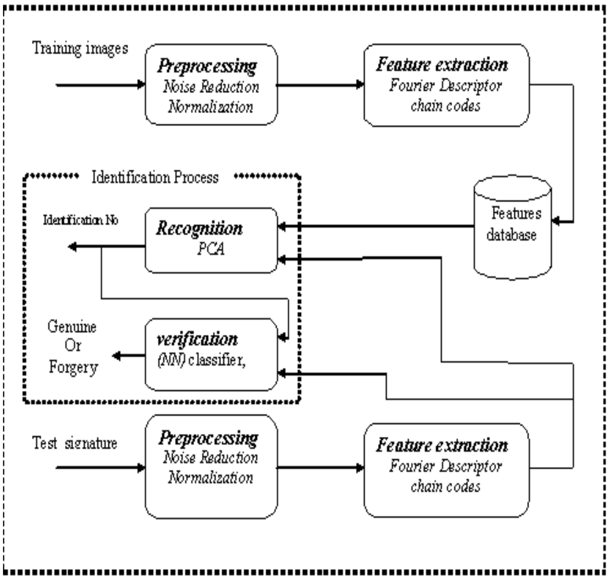
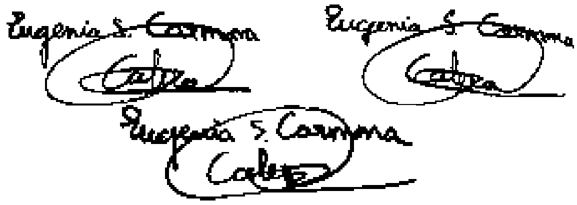


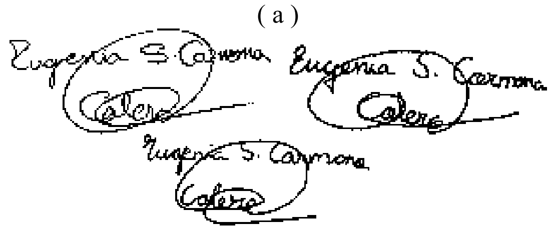
Figure 1 : The flow diagram for the proposed method

2- Database

The signature database consists of 2400 signature images, scanned at a resolution of 300 dpi,8-bit gray-scale. They are organized into 50 sets, and each set corresponds to one signature enrollment. There are 24 genuine and 24 forgery signatures in a set. Each volunteer was asked to sign his or her own signatures on a white paper 24 times. After this process had been done, we invited some people who are good at imitating other's handwritings. An examples of the database image are shown in figure 2



(a)



(b)

Figure 2 . (a) Genuine and (b) forgery signatures.

3- Signature image Preprocessing

Any image-processing application suffers from noise like touching line segments, isolated pixels and smeared images. This noise may cause severe distortions in the digital image and hence ambiguous features and a correspondingly poor recognition and verification rate. Therefore, a preprocessor is used to remove noise. Preprocessing techniques eliminate much of the variability of signature data.

3-1 Noise Reduction

Standard noise reduction and isolated peak noise removal techniques, such as median-filtering and average filtering (Gonzalez and Wintz, 1987) , are used to clean the initial image.

3-2 Normalization

The next step in the Signature recognition process is image normalization .Normalization is used to standardize the intensity values in an image by adjusting the range of gray-level values so that it lies within a desired range of values. Let I(i, j) represent the gray-level value at pixel (i, j), and N(i, j) represent the normalized gray-level value at pixel (i, j). The normalized image is defined as:

$$N(i,j)=\begin{cases} M_0+\sqrt{\dfrac{v_0(I(i,j)-M)^2}{v}} & \text{if } \quad I(i,j)>M \\ M_0-\sqrt{\dfrac{v_0(I(i,j)-M)^2}{v}} & \text{otherwise} \end{cases}$$

where M and V are the estimated mean and variance of I(i,j) , respectively , and M_0 and V_0 are the desired mean and variance values, respectively.

4- Features extraction

The choice of a powerful set of features is crucial in signature verification systems. In our system, we use Fourier descriptor and chain code features.

4-1 chain codes

chine code are used to represent a boundary by a connected sequence of straight-line segment of specified length and direction. Typically, this representation is based on 8-connectivity of the segment. The direction of each segment is coded by using a scheme shown in figure 3. Chain codes based on this scheme are referred to as Freeman chain code (Gonzalez and Wintz, 1987) .

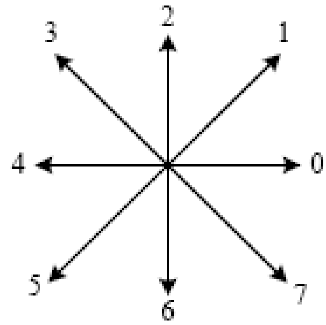


figure 3 : Direction number for 8–directional chain code

4-2 Fourier Descriptor

For any derived 1D signature function $u(t)$, its discrete Fourier transform is given by

$$a_n = \frac{1}{N}\sum_{t=0}^{N-1} u(t)\exp(-j2\Pi nt/N)$$
$$n = 0,1,\dots,N-1$$

This results in a set of Fourier coefficients { a_n }, which is a representation of the signature region . Since image generated through rotation, translation and scaling (called similarity transform of a image) of a same image are similar images , a image representation should be invariant to these operations. The selection of different start point on the image boundary to derive $u(t)$ should not affect the representation. From Fourier theory, the general form for the Fourier coefficients of a contour generated by translation, rotation, scaling and change of start point is given by :

$$a_n = \exp(jnt)\times\exp(j\phi)\times c\times a_n^{(0)} \qquad n \neq 0$$

where a_n^0 and a_n are the Fourier coefficients of the original image and the similarity transformed image , respectively; $\exp(jnt)$, $\exp(j\Phi)$ and s are the terms due to change of starting point, rotation and scaling. Except the DC component (a_0), all the other coefficients are not affected by translation. Now considering the following expression

$$b_n = \frac{a_n}{a_0} = \frac{\exp(jnt)\times\exp(j\phi)\times c\times a_n^{(0)}}{\exp(jt)\times\exp(j\phi)\times c\times a_0^{(0)}}$$
$$= \frac{a_n^{(0)}}{a_0^0}\exp[j(n-1)t] = b_n^{(0)}\exp[j(n-1)t]$$

where b_n and b_n^0 are normalized Fourier coefficients of the derived image and the original image , respectively. The normalized coefficient of the derived image b_n and that of the original image b_n^0 have only difference of $\exp[j(n-1)t]$. If we ignore the phase information and only use magnitude of the coefficients, then $|b_n|$ and $|b_n^0|$ are the same. In other words, $|b_n|$ is invariant to translation, rotation, scaling and change of start point. The set of magnitudes of the normalized Fourier coefficients of the signature image { $|b_n|$, $0 < n \le N$ } can now be used as signature image descriptors, denoted as $\{FD_n 0 < n \le N\}$.

5- signature identification

Signature identification can be classified into two different problems: recognition and verification. Recognition selects the author of a sample from among a group of writers, while verification confirms or rejects a written sample, as shown in Figure 1. So, the question that a recognizer answers is: who is the writer? While the question that the verifier answers is: Is this the writer's true signature?

5-1 Recognition process

The recognition process classifies a given sample as belonging to one of the known writers in the database. In the recognition process we use principal component analysis.

5-1-1 PCA in signature recognition

Let features vector extracted from signature images is Γ_i . be one-dimensional image of N- elements and suppose we have M images (i = 1,2..M) . The main idea of PCA is to find the vector that beast account for distribution of these vectors within the entire image space. These vectors define the subspace of signature images features , called as " signature space " each vector of length N elements , describes a N image, and is a linear combination of the original signature vectors . Because these vectors are the eigenvectors of the covariance matrix corresponding to the original signature image features vectors , and because they are similar to signature image features in appearance, they are referred to as " eigensignature"

Let the training set of signature vectors be $\Gamma_1, \Gamma_2, \Gamma_3, \ldots \Gamma_M$ the average vector of the set is defind by

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n$$

. Each vectors differs from the average by the vector $\Phi_n = \Gamma_n - \Psi$

Let t he vectors μ_k ,and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix [1].

$$c = \frac{1}{M} \sum_{n=1}^{m} \Phi_n \Phi_n^T = AA^T$$

Where

$$A = [\Phi_1, \Phi_2, \Phi_3 \ldots \Phi_M]$$

In order to perform PCA , its necessary to find μ_k and λ_k. Because the dimensionality of N2 Of the matrix C is large even for a small images, and computation of eigenvectors using traditional method is complicated, dimensionality of matrix C is reduced using the decomposition describe in (Kirby M and Sirovich, L.,1990). Found eigenvectors $\mu = (\mu_1, \mu_2, \ldots \mu_N)^T$ are normed and stored in decreasing order according to the corresponding eigenvalues. Then these vectors are transposed and arranged to form the row-vectors of transformation matrix ω_n (eigensignature)

5-1-2 Using eigensignature to classify a signature image

A new signature image FD features Γ is transformed into its eigensignature components (projected onto " signature space") by a simple operation (Turk M. and A. Pentland. 1991).

$$\omega_n = \mu_n (\Gamma - \Psi) \qquad n = 1,2.,\ldots, M'$$

This describe a set of point-by-point image multiplications and summations. The weights from a vector $\Omega^T = [\omega_1, \omega_2, \ldots, \omega_{M'}]$ that describe the contribution of each eigensignature in representing the signature image, treating the Eigensignature as a basis set for signature images. The vector may thin used by a standard pattern recognition algorithm to find which of the number of predefined signature classes, if any , best describe the signature image the next section discuses some distance measured can be used .

5-1-3 Distance measures

Let X, Y be eigensignature feature vectors of length n. Then we can calculate the following distances between these feature vectors.

Minkowski distance (LP matrices)

$$d(X,Y) = L_p(X,y) = \Big(\sum_{i=1}^{n} \left| x_i - y_i \right| \Big)^{1/P}$$

Manhattan distance (L1 matrices , city block distance)

$$d(X,Y) = L_{p=1}(X,y) = \sum_{i=1}^{n} \left| x_i - y_i \right|$$

Euclidean distance (L2 matrices)

$$d(X,Y) = L_{p=2}(X,y) = \sqrt{\sum_{i=1}^{2} (X_i - y_i)^2}$$

Angle – based distance

$$d(X,Y) = -\cos(X,Y)$$

$$\cos(X,Y) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}}$$

Correlation coefficient- based distance

$$d(X,Y) = -r(X,Y)$$

$$r(X,Y) = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{\left(n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2\right) \left(n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2\right)}}$$

Modified Manhattan distance

$$d(X,Y) = \frac{\sum_{i=}^{n} \left| x_i - y_i \right|}{\sum_{i=1}^{n} \left| x_i \right| \sum_{i=1}^{n} \left| y_i \right|}$$

Modified SSE-based distance

$$d(X, Y) = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}$$

5-2 Verification process

The goal of an automatic signature verification (ASV) system is to confirm or invalidate the presumed identity of the signer from information obtained during the Recognition of the signature. We designed a multilayer feed forward artificial neural network for verification of off-line digitized signatures. The proposed ANN consists of 28 input variables, 50 hidden neurons, and 2 output variables and it is designed to verification one signature at a time. Back propagation algorithm is used for training.

6- Experimental Results

This section reports some experimental results obtained using our method . In the following experiments, a total of 2400 signature images. The experimental platform is the Intel core 2 duo 1.83 GHZ processor, 1G RAM, Windows vista , and the software is Matlab 7.0.0.1. The recognition performance is evaluated using different distance measure as present in Table 1.

Distance measures	Correct recognition rate
Minkowski distance	92.6%
Manhattan distance	96.2%
Euclidean distance	95.4%
Angle – based distance	93.4%
Correlation coefficient-based distance	92.2%
Modified Manhattan distance	95.6%
Modified SSE-based distance	88.8%

Table 1 : Results obtained using various distance measure

The performance of signature verification is estimated with False acceptance ratio and False rejection ratio. False acceptance ratio (FAR) is the ratio of accepting an unregistered signature image and rejecting a registered one. False rejection ratio (FRR) is the ratio of rejecting a registered signature image and accepting an unregistered one. Table 2 present the verification process results.

FAR	FRR
2.6%	1.6%

Table 2 : Results obtained on verification process

Table 3 compare the performance of our proposed methods with other published works.

Method	Result
Kashi et al. [24]	Equal error rate of 2.5%, at 1% false rejection, error rate is 5%.
Pawlidis et al. [25]	A 78.9% accurate system, with 18.3% inconclusive data and 2.8% false recognition.
Wu et al. [26]	The system has a correct acceptance of 86.5% and a correct rejection rate of 97.2%.
Lecce et al. [27]	The system has the following error: 3.2% false rejection, 0.55% false acceptance with 3.2% rejection rate.
Sebastian et al. [28]	The system performed with an accuracy rate of 98%.
Aguilar et al. [29]	Relative improvements in the verification performance as high as 51% (skilled) and 78% (random) are obtained as compared to published works.
Hairong et al. [30]	The average error rate can reach 5%.
Audet et al. [31]	The average error rate is of about 14% for all cases.
Ibrahim et al. [32]	An equal error rate of 26.7% and 5.6% was achieved for skilled and random forgeries, respectively.
Propsed method	The system has the following error: 3.8% false acceptance rate, 2.6% and false rejection rate with 1.6%.

Table 3: Compare the performance of the proposed methods with other published works

7- Conclusion

In this paper we present a new method for off-line signature identification. Fourier Descriptor and Chain Codes features are used in this method for represent Signature image. Signature identification classified into two different problems: recognition and verification. In recognition process we used Principle Component Analysis. In verification process we designed a multilayer feed forward artificial neural network. Different distance measured to evaluate the results of recognition process and Manhattan distance give the best results. Our method give a good results in verification process because FAR = 2.6% and FRR= 1.6% . All experimental results have demonstrated that the proposed method achieves high performance in both speed and accuracy

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