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Offline Handwritten Signature Identification using Grid Gabor Features and Support Vector Machine

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Abstract: *In this paper, a new method for signature identification based on wavelet transform is proposed. This method uses Gabor Wavelet Transform (GWT) as feature extractor and Support Vector Machine (SVM) as classifier. In proposed method, first signature image is normalized by size and then image is enhanced to remove noise. After pre-processing, a virtual grid is placed on signature image and Gabor coefficients are computed on each point of grid. Next, all Gabor coefficients are fed to a layer of SVM classifiers as feature vector. The number of SVM classifiers is equal to number of classes. Each SVM classifier determines that does the input image belong to corresponding class or not.*

The main characteristic of proposed method is independency to nation of signers. Two experiments on two signature sets were done. The first is on a Persian signature set and other is on a Turkish signature set. Based on these experiments, identification rate have achieved 96% and more than 93% on Persian and Turkish signature set respectively.

Keywords: Signature Identification, Gabor Wavelet, Grid Features, Support Vector Machine.

1. Introduction

Nowadays, person identification (recognition) and verification is very important in security and resource access control. For this purpose, the first and simple way is to use Personal Identification Number (PIN). But, PIN code may be forgotten. Now, an interesting method to identification and verification is biometric approach. Biometric is a measure for identification that is unique for each person. Always biometric is together with person and cannot be forgotten. In addition, biometrics usually cannot be misused. Handwritten signature is one of formers biometrics; however, some researchers believe that handwritten signature is not a real biometric.

Handwritten signature identification is simple, inexpensive, non-intrusive and acceptable from society [1]. Nevertheless, it has some drawbacks: lower identification rate with respect to other biometrics, non-linear changes with size changing and dependency to time and emotion [1,2]. Another problem of processing the handwritten signature is that the signature of each nation is different with another nation. For example, European signature is same as his/her name writing in a special style and Persian signature contains some curves and symbols [3].

There are many applications for signature identification: in banking, user login in computer or Personal Digital Assistant (PDA) and access control. In [4] an intelligent signature processing system for banking environment was presented that has named as AutoSIG system. More applications of signature identification have been discussed in [3].

There are two modes for signature identification and verification: static or off-line and dynamic or on-line. In static mode, the input of system is a 2-dimentional image of signature. Contrary, in dynamic mode, the input is signature trace in time domain. In dynamic mode, a person sign on an electronic tablet by an electronic pen and his/her signature is sampled. Each sample has 3 attributes: x and y in 2-dimentions coordinates and t as time of sample occurrence. So, in dynamic mode, the time attribute of each sample help us to extract useful information such as start and stop points, velocity and acceleration of signature stroke. Some electronic tablets in addition of time sampling, could digitize the pressure. This additional information existing in dynamic mode, increase identification rate with respect to static mode. Although the identification rate of dynamic mode is higher than static mode, but dynamic mode has a main disadvantage: it is on-line. So, it cannot be used for some important applications that the signer could not be presented in singing place.

2. Related Works

The problem of automatic signature identification has received little attention in comparison with the problem of signature verification despite its potential applications for accessing security-sensitive facilities and for processing certain legal and historical documents.

Cavalcanti et al [2] investigates the feature selection for signature identification that signature set contains different signature size. The size of signatures in each class is small, medium and big. This study used structural features, pseudo-dynamic features and five moments and selected some classifier independent features to increase performance. Finally has been advised to normalize signature images before identification.

Mohamadi [5] has presented a Persian static signature identification system using Principle Component Analysis (PCA) and Multi Layered Perceptron (MLP) neural network. In training phase, PCA construct some eigen vectors based on training set images. In test phase, PCA extracts the eigen value of each eigen vector from a new signature image. These eigen values use as feature and are fed to a MLP classifier. For experiment, 20 classes of Persian signatures were used that there are 10 signatures for training and 10 signatures for test per class. Identification rate has been reported as 91.5%.

Sigari and Pourshahabi [3] have investigated signature identification and verification using signal-processing approaches. In their thesis, they compared Discrete Cosine Transform (DCT), Hough transform, Radon transform and GWT and finally proposed GWT for feature extraction in signature identification and verification. They used GWT as feature extractor and Euclidean distance as classifier in both identification and verification. A virtual grid is placed on the image of signature and some coefficients are computed by GWT on each point of grid. For experiment, a Persian signature set was used same as signature set that in [5] has been used. Identification rate was 99.5%.

Ozgunduz et al have presented [6] an off-line signature verification and recognition system using the global, directional and grid features. SVM was used to verify and classify the signatures and a classification ratio of 95% was obtained. As the recognition of signatures represents a multi class problem, SVM's one-against-all method was used. In addition, this method performance was compared with MLP. This comparison shows that SVM has better performance than MLP.

Martinez et al [7] have presented an efficient off-line human signature recognition system based on SVM and have compared its performance with a MLP. In both cases, two approaches to the problem was used: (1) construction of each feature vector using a set of global geometric and moment-based characteristics from each signature and (2) construction of the feature vector using the bitmap of the corresponding signature. Signature set contains 228 signatures in 38 classes. In training phase, only one signature has been used for each class. Results show that SVM, which achieves up to 71% recognition rate, outperforms MLP with 47% recognition rate.

Kaewkongka et al [8] have described a method of off-line signature recognition by using Hough transform to detect stroke lines from signature image. The Hough transform is used to extract the parameterized Hough space from signature skeleton as unique characteristic feature of signatures. They have used a MLP neural network as classifier. The system has been tested with 70 test signatures from different persons. The experimental results reveal the recognition rate 95.24%.

3. Preprocessing

Before any processing, some preprocessing operations have to do on signature images. Finding the outer rectangle of signature, image enhancement and size normalization are the preprocessing operations. Figure 1 shows a sample original signature before preprocessing.

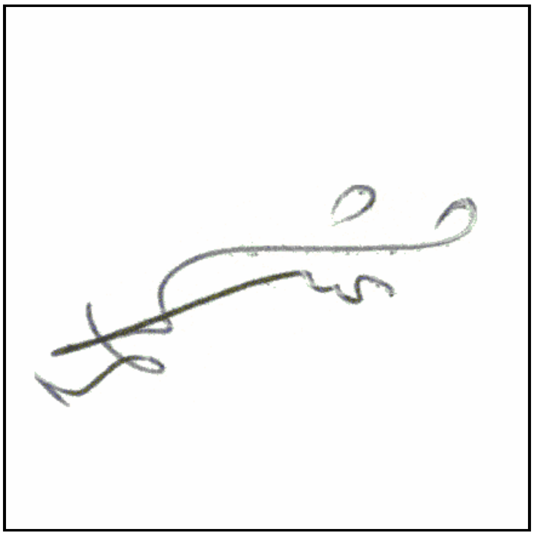

Figure 1. An original sample signature

3.1. Finding the outer rectangle

First step of preprocessing is to find the outer rectangle of the signature. Outer rectangle is a rectangle with the least size that all pixels of signature are in it. The outer rectangle can be found using horizontal and vertical projection of binary image. Binarization of signature image have been done using Otsu binarization algorithm [9]. In Figure 2, horizontal and vertical projections of binary image are shown respectively. In Figure 3, signature image is placed in outer rectangle.

3.2. Image enhancement

Next step is image enhancement. The obtained threshold from Otsu binarization algorithm is used in image enhancement and named as T. Background image is white. Therefore, if the gray level of a pixel is more than T, it will change to white (255), else it will not have any change. The result of image enhancement is shown in Figure 4.

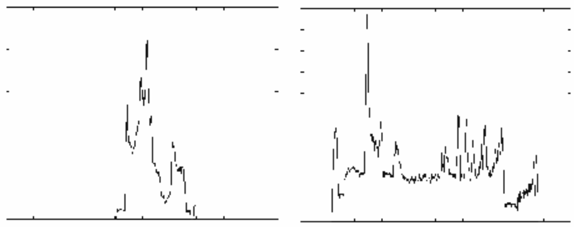

Figure 2. Horizontal (left) and vertical (right) projection of signature image

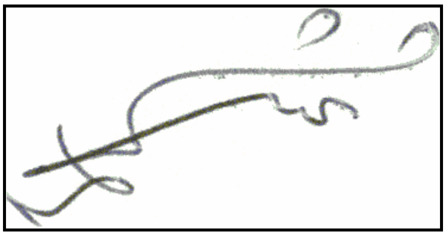

Figure 3. Finding the outer rectangle of signature

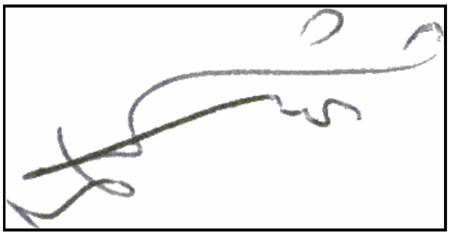

Figure 4. Image enhancement

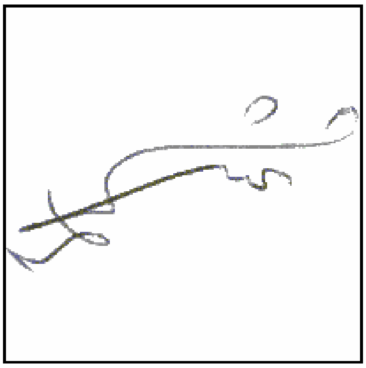

Figure 5. Size normalization

3.3. Size normalization

The last preprocessing step is size normalization. It is the most important preprocessing phase that affect identification rate directly [2].

If the width of image is more than the height, the normalization is based on width; else, it is based on height. In this paper, all signature images have to normalize to 200 x 200 pixels. So, the image will be resized based on the long dimension of image to set it to 200 pixels. Other dimension of image will be grown with white line padding in each side symmetrically. Figure 5 shows the result of size normalization.

4. Feature extraction

GWT have been used to extract feature from signature images. 2-dimnesional Gabor wavelet filter in point (x, y) has five parameters and is defined as below [10]:

$$w(x, y) = \exp\left(\left(x'^2 + \gamma^2 y'^2\right)/2\sigma^2\right)\cos(2\pi x'/\lambda + \varphi) \quad (1)$$

x' and y' are computed using equation (2) and (3) respectively.

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

θ specifies the orientation of the wavelet. This parameter rotates the wavelet about its center. The orientation of the wavelets dictates the angle of the edges or bars for which the wavelet will respond. In most cases theta is a set of values from 0 to π. Values from π to 2π are redundant due to the symmetry of the wavelet.

λ specifies the wavelength of the cosine wave, or inversely the frequency of the wavelet. Wavelets with a large wavelength will respond to gradual changes in intensity in the image. Wavelets with short wavelengths will respond to sharp edges and bars.

φ specifies the phase of the sinusoid. Typically, Gabor wavelets are based on a sine or cosine wave. In the case of this algorithm, cosine wavelets are thought to be the real part of the wavelet and the sine wavelets are thought to be the imaginary part of the wavelet. Therefore, a convolution with both phases produces a complex coefficient. The mathematical foundation of the algorithm requires a complex coefficient based on two wavelets that have a phase offset of $\pi/2$, i.e. $\varphi \in \{0, \pi/2\}$. Therefore, assuming $\varphi \in \{0, \pi/2\}$ is led to only one complex Gabor coefficient.

σ specifies the radius of the Gaussian. The size of the Gaussian is sometimes referred to as the wavelet's basis of support. The Gaussian size determines the amount of the image that effects convolution. In theory, the entire image should effect the convolution; however, as the convolution moves further from the center of the Gaussian, the remaining computation becomes negligible. This parameter is usually proportional to the wavelength, such that wavelets of different size and frequency are scaled versions of each other, i.e. $\sigma = c\lambda$.

γ specifies the aspect ratio of the Gaussian. In most Gabor wavelets this parameter is set to 1.

To extract features from signature image, a virtual grid is placed on signature image and Gabor coefficients are computed on each point of grid by convolution. Convolution is between Gabor filter and a sub image around point (x, y).

The virtual grid size is 9 x 9, therefore, distance between successive grid points in vertical or horizontal direction is 20 pixels. Figure 6 shows the virtual grid on signature image.

In each point of virtual grid, 12 complex Gabor coefficients are computed assuming $\lambda \in \{2, 2\sqrt{2}, 4\}$ and $\theta \in \{0, \pi/4, \pi/2, 3\pi/4\}$. Other Gabor filter parameters are assumed that are constant: $\varphi \in \{0, \pi/2\}$, $\sigma = 2\lambda$ and $\gamma = 1$. This means that for each grid point, 3 frequencies in 4 orientations and 2 phases are investigated. Therefore, for all grid points of an image, 972 complex coefficients are computed. Absolute of these coefficients are the features that are fed to SVM classifiers.

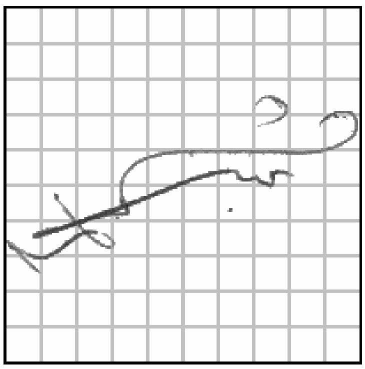

Figure 6. Virtual grid on signature image

5. Classification

Classification is the last step of signature identification. For classification of signature classes, a layer of SVM classifier has been used.

The number SVM classifier in classification layer is equal to number of signature classes.

Vapnik [11] introduced the concept of SVM in late of 1970's. SVM, based on a solid mathematical foundation, attempts to solve a universal problem of classification. The basic idea of SVM is deceptively simple. Given a set of vectors in R^n, labeled +1 or -1 that are 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.

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 identification, number of SVM classifiers is equal with number of signers. A SVM classifier is used per class that classifier output is -1 or +1. When all classifier outputs except only one classifier are -1, the class of input signature will be the corresponding class of classifier that generates +1. When the output of all classifiers are -1 or two or more classifier outputs are +1, the input signature will not belong to known classes.

Third order polynomial is selected for kernel of SVM classifiers. Increasing or decreasing the order of polynomial kernel will eventuate to lower identification rate. In addition, other kernels such as RBF or MLP have lower identification rate.

6. Experimental result

Two experiments were done to evaluate proposed method for signature identification. The first experiment was on a Persian signature set. This signature set is same as signature set using in [5]. It contains 20 classes and 20 signatures per class. For each class, 10 signatures for training and 10 signature for test were used. Identification rate is 96%.

Other experiment was on a Turkish signature set. This set is same as the signature set that used by Ozgunduz et al in [6]. It contains 40 classes and 16 signatures per class. 8 signatures for training and 8 signatures for test are used for each class. Identification rate is up to 93%.

7. Conclusions

We proposed a new signature identification method using GWT and SVM and evaluated it on two signature sets. First experiment was on Persian signatures. Identification rate on this set is 96%. Our proposed method outperforms the identification method in [5] for Persian signature identification. Other experiment was on a Turkish signature set that be used in [6]. Ozgunduz et al have achieved to 95% identification rate on this set, but our method could identify signatures with 93% true rate.

Turkish signatures are very like to other European signatures, because of using the signer name as signature. Experiments show that our proposed method has acceptable results on both Persian and Turkish signatures. Therefore, it can be used to identify signatures of many nations. This is the main advantage of our method that is an important feature for a signature identification system.

8. References

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