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An analytical approach towards Offline Handwritten Signatures Verification using Wavelets transforms and other relevant techniques

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Abstract: The various researches conducted for classification of handwritten signatures of people have shown that the task is difficult because there are intra personal differences among the signatures of the same person. The signatures of the same person vary with time, age of the person and also because of the emotional state of a person. The task of classifying the skilled forgery signatures is all the more challenging because they are the result of lot of practice, closely imitating the signature. Neural networks based classifiers have proved to yield very accurate results. This paper for offline signature verification uses the images stored in the GPDS database. The preprocessed images are decomposed using discrete wavelet transform up to the maximum level.

In this paper, we are studying some new methods for offline handwritten signature identification and verification based on wavelet transforms. The whole idea is offering a simple and robust method for extracting features based on Wavelet transform. As it was pointed out earlier, one of the advantages of this system is its capability of signature identification and verification of different nationalities; thus it has been tested on four signature dataset with different nationalities including Iranian, Turkish, South African and Spanish signatures.

Keywords: Signature Identification; Verification; Multi-Resolution Analysis; Wavelet transform.

INTRODUCTION

Handwritten signatures are an age old accepted means of a person's identification in government, legal and commercial transactions. As a result, the signatures are highly vulnerable and are often forged and misused. Biometrics is the technological means that enables the identification or true verification of an individual from its physical or behavioral characteristics depending on their nature. It is classified into two categories namely behavioral and physiological. Where physiological biometrics measure some physical features of the subject like fingerprints, iris, hand and finger geometry which are stable over time. With the use of edge direction histogram derived from the edge map of the picture, only a small number of most possible intra prediction modes are chosen. Therefore the fast mode decision algorithm helps to speed up intra coding significantly.

There are many situations where a small piece of information like handwritten signatures is used for identification. It is very essential to correctly classify whether a given signature is a genuine or a forgery. The data used for classification comes from either of the following two approaches.

(i) Online Approach

(ii) Offline Approach

Off-line verification deals with signatures that have been written on paper and digitized by scanning them. Here the dynamic information is missing which results in low accuracy results. But the offline approaches are needed in many situations. Online approaches use a device or a digitizing surface to capture dynamic features like pressure, speed, direction etc which result in higher accuracies. The forgeries related to handwritten signatures are classified into three types.

A. Casual Forgery

The signer observes the signatures of others closely for a very brief moment and then puts them in his own style without any prior experience.

B. Skilled Forgery

This type of forgery is deliberately created by some professional forgers and they would have sufficiently practiced for a long time to forge other's signatures. These are very hard for detection and hence quite challenging.

C. Random Forgery

The signer or the forger creates it by using the name of the victim in his own style to create a forgery known as the simple forgery or random forgery. The signatures are used for identification because it is a well accepted form of identification in the society and a non invasive method which does not annoy an individual being verified. However challenges are many. There are disadvantages like there are intra personal variations in an individual's signature and sometimes a greater variability can be observed in signatures according to age, time, habits or emotional state.

LITERATURE REVIEW

The use of signatures is one of the most employed mechanisms to verify the identity of individuals; the whole bank-check payment system is based on the use of signatures. In this context, computer-based signature verification is an active research area in biometry. Lot of experiments and research work has done within last few years regarding off-line and on-line signature verification. Though online verification provides better result than off-line system but off-line verification is also important in some situations where the person is not present physically. The past experiments work fine to detect simple and random forgery. But have lesser success rate to detect skilled School of Education Technology, Jadavpur University 98 forgery [1].

Frias-Martinez et al proposed an offline handwritten signature identification system using Support Vector Machines (SVM) and compared this system with another system which used Multi-Layer Perceptrons (MLP) as classifier. Both of these systems have been tested with two different feature extraction approaches: (1) extracting some global and moment-based features, (2) using raw bitmap data of signature image as feature vector. Their proposed system used just one signature per class as training data similar to the practical systems. Experimental results show that SVM is better than MLP for classification in both approaches of feature extraction. Ozgunduz et al described an offline handwritten signature identification and verification system using the global, directional and grid features of signatures. Before extracting features, all signature images were pre-processed by background elimination, noise reduction, width normalization and thinning the stroke.

Many signature verification systems have been developed in the past [2]. Signatures that have already been written on paper, dynamic information cannot be obtained from it. However, the writing force and habit of a certain person could be reflected by his handwriting, therefore, this paper extracts the dynamic information for verification [3]. The region with low gray level is defined as low gray level region.

MLP. Kalera et al. presented a quasi multi resolution approach for offline signature identification and verification. First, all signature were normalized by rotation. Then GSC (Gradient, Structural and Concavity) features are extracted and fed into a Bayesian classifier. Gradient features are local; and structural and concavity features are global. So feature extraction acts like a multi-resolution processing. Deng et al proposed a wavelet-based offline signature verification system. This system extracts robust features that exist within different signatures of the same class and verify whether a signature is a forgery or not. After pre-processing stage, the system starts with a closed contour tracing algorithm to extract closed contour of signature. The curvature data of the closed contours are decomposed to low and high frequency bands using wavelet transform [4].

Herbst et al designed a signature verification system using Discrete Radon Transform and Dynamic Programming. First, all signatures are normalized by Translation, Rotation and Scaling. Then Radon Transform has been applied to extract features. A grid relation between features of input signature and features of reference signatures has been created using Dynamic Programming. Afterward, matching analysis was done to accept or reject the input signature. Coetzer et al [5] have used Radon Transform and Hidden Markov Model (HMM) for offline signature verification. When a signature is written on white paper with dark pen, the low gray level region reflects the areas with high pressure. The process of signature verification should be able to detect forgeries. Forgeries can be classified into three main categories [6]. First one is random forgery, which is written by the person who doesn't know the shape of original signature. The second, called simple forgery, which is represented by a signature sample, written by the person who knows the shape of original signature without much practice. The last type is skilled forgery, represented by a suitable imitation of the genuine signature model. Each type of forgery requires different types of verification approach.

Kiani et al extracted appropriate features by using Local Radon Transform applied to signature curvature and then classified them using SVM classifier. Their proposed method is robust with respect to noise, translation and scaling. Experimental results were implemented on two signature databases: Persian (Iranian) and English (South African). Pourshahabi et al presented an offline signature identification and verification using Contourlet Transform. Contourlet is a two dimensional multi-resolution transform that extracts curves from an image with different thicknesses and curvatures. In this paper, after signature normalization, features were extracted using Contourlet Transform and then classified by Euclidean Distance. This method was applied on two signature databases: Persian (Iranian) and English (South African) [7].

WAVELETS TRANSFORM

Wavelet transform is especially suitable for any application where the information available is hardly represented by functions. Offline handwritten signatures classification is also one such application. The wavelets can match any signal by various versions of the mother wavelet with various translations and dilations. The various characteristics of wavelet transforms like multiresolution ability, linear nature, and orthogonality make it a desirable technique in many applications and hence we have used this method in our paper for feature extraction.

Wavelets provide the representation and analysis of signals at more than one resolution which is called as multi-resolution ability. The advantage of multi-resolution analysis is that the features which go undetected at one resolution may be detected at other resolutions. Wavelets can analyse both stationary and non-stationary signals. By stretching and shifting the wavelet, it can be made to correlate with any event which is of interest so that the frequency and time of the event can be exactly measured. When a signal is decomposed using the wavelet transform, both detail coefficients and approximation coefficients are obtained. When the wavelet is stretched, the longer is the portion of the signal being compared with it and they represent the low frequency components which are nothing but slowly varying parts of the signal. When a wavelet is shrunk, the smaller portion of the signal is being compared to it and they represent high frequency components which are the rapidly changing parts of the signal. Continuous and Discrete Wavelet Transforms are possible [8].

Wavelets Theory

Unlike sinusoids, a wavelet is a waveform of limited duration whose average value is zero. The sinusoids theoretically extend from minus infinity to plus infinity where as the Wavelets have a beginning and an end. The multiresolution feature is well supported by Wavelets and hence the representation and analysis of signals at more than one resolution is possible. The multi resolution analysis is capable of ensuring that the features which go undetected at one resolution will be detected at another. Wavelets can work with both stationary and non stationary signals which change frequency over time and can detect anomalies, pulses and events that exist within the signal being analyzed. This is possible because the Wavelet can be stretched or scaled to match the same frequency as the anomaly, pulse or event. Wavelets can also be shifted in time domain to align with the event. Having the knowledge of how much the wavelet was stretched or shifted to align or correlate with the event helps to know the frequency and time of the event.

The stretching and shifting of wavelet calculates an index which is a measure of resemblance between the signal and the wavelet located at a particular position and a particular scale. The indexes are termed as Wavelet coefficients and larger the index higher is the resemblance, otherwise it is slight. The higher scales correspond to the most "stretched" wavelets and the higher the stretching of the wavelet, the longer is the portion of the signal with which it is being compared and thus the coarser the signal features being measured by the wavelet coefficients. There is a definite relationship between wavelet scales and frequency as revealed by wavelet. Low scale indicates a compressed wavelet which are the rapidly changing details or in other words high frequency components. High scale indicates a stretched wavelet which are slowly changing or coarse features or in other words low frequency. Wavelet analysis gives a time-scale view of the signal. There are two types of Wavelet transforms possible and they are Continuous Wavelet Transform and Discrete Wavelet Transform [9].

Continuous Wavelet Transform

The continuous wavelet transform is going to calculate wavelet coefficients at each possible scale which is indeed tedious. This transforms sums over the all time of the signal multiplied by scaled, shifted versions of the wavelet. This process produces wavelet coefficients that are a function of scale and position. The scaled and shifted wavelet is multiplied with the signal and summed for the entire time of the signal. This transform is continuous in the sense that the signal is analysed fully by the wavelet.

Discrete Wavelet Transform

Calculating wavelet coefficients at every possible scale is a tedious task and it generates a lot of data. In order to avoid this the Discrete Wavelet Transform the wavelet coefficients are calculated only at scales and positions which are chosen based on powers of two and they are called dyadic scales and positions, then the analysis will be much more efficient and just as accurate [10].

Daubechies Wavelet Transform

Daubechies wavelets are denoted as dbN where N is the order of the wavelet. This wavelet is both regular and orthogonal. It has compact support and both the continuous wavelet transform and discrete wavelet transforms are possible. Since the wavelets are regular, the regularity of a signal can be easily measured by analyzing the wavelet coefficients. Some of the properties of the Daubechies wavelet are as follows:

- The fine scale amplitudes are very small in regions where the function is smooth
- They have identical forward and backward filter parameters
- They have fast, exact reconstruction
- They have compact support
- They possess a finite number of filter parameters and fast implementations
- They have high compressibility
- They are very asymmetric

PROPOSED SYSTEM

The proposed system is consisting of three stages: (1) pre-processing stage, (2) feature extraction stage and (3) classification stage. In pre-processing stage, noise elimination of the signature image is performed. Rotation and size normalization of the signature image are also achieved in this stage. Feature extraction stage is based on the computation of Gabor wavelet coefficients on specific points of the pre-processed signature image. Extracted features (wavelet coefficients) are then fed to a classifier. In the signature identification system, the identity of the signer is recognized in the classification stage whereas; in the signature verification system the forgery or genuine type of the signature is determined. The diagram of the proposed system is shown in Figure 1 [11].

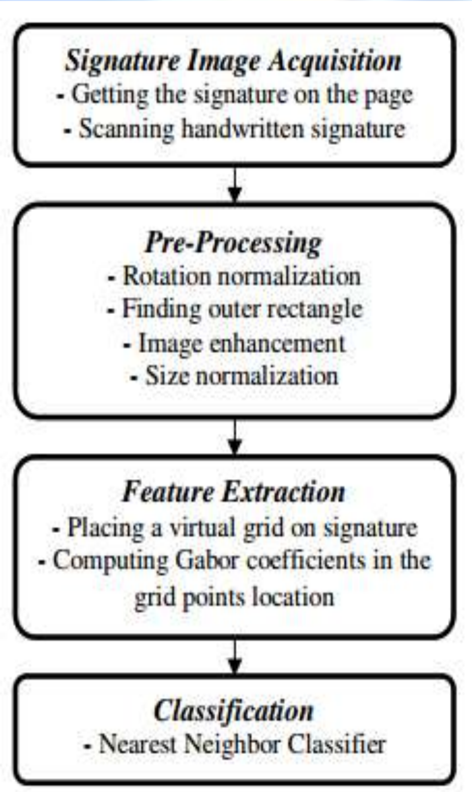

Fig 1: Flowchart of the proposed system [19].

A. Preprocessing

There are signatures belonging to 640 subjects where for each person there are 24 genuine signatures and 30 forgery signatures available in the database. From the database four genuine signatures and four forgery signatures of each person are considered for the study. All the signature images are first converted into binary images. Bounding rectangles are put over the signature images to cover only the signature area. Once the bounding rectangles are put, normalization is done in order to resize the signature images with the aspect ratio maintained of the original signature. Bilinear interpolation method has been used for resizing. After normalizing the size, the images have been thinned in order to eliminate the effect of using different types of pens [12].

B. Feature Extraction

The preprocessed images of the signatures after the steps of normalizing and thinning are decomposed by db4 wavelet transform. The resulting wavelet coefficients are large in number and in order to choose the important ones and hence reduce the dimensionality of feature space, the principal component analysis (PCA) is carried out for both approximation and detail coefficients. The principal component analysis is done using standardized variables which is based on correlations. As a result of principal component analysis, scores are produced. These scores are the data formed by transforming the original data into the space of the principal components [13].

The first ten values of latent and Hotelling'sT2 are chosen for the approximation and three detail coefficients namely horizontal, vertical and diagonal. These first ten values corresponding to four types of Wavelet coefficients are obtained as mentioned above for 4 genuine and 4 forgery signatures of each person and these form the feature vector for training the SVM classifier and classification is done [15]. Each signature is represented by total 80 features (10 latent vector values and 10 Hotelling's T2 values each for four types of wavelet coefficients approximation, horizontal, vertical and diagonal). Sequential Minimum Optimization (SMO) technique is used in the SVM classifier for faster optimization. SVM classifiers have been designed using both a linear kernel and a non linear kernel namely Gaussian Radial Basis Function kernel. Matlab software has been used for implementation. In this paper, an attempt has been made to understand the performance of linear and non linear kernels over the same dataset with the same number of features [16].

C. Neighbour Classification

In a sample, there are signatures belonging to a total of 640 people in the database. There are 24 genuine signatures and 30 forgeries for each person in the database. The database consists of 34560 signatures (640*(24+30)).This database is divided into training and testing datasets [17]. The 4 genuine signatures and 4 forgery signatures of each person form the training set. They have been preprocessed and then applied the Daubechies wavelet transform in order to extract the features. The remaining signatures of each person form the testing set. The FAR and FRR in case linear kernel are 13% and 10% respectively. The FAR and FRR in case of the non linear kernel i.e. Gaussian Radial basis function are 15% and 12% [18].

CONCLUSIONS

The review, presented in this paper, is employing wavelet transform technique for offline handwritten signatures verification. Unlike many current approaches, the proposed method is independent of the shape and the style of signature. The proposed system has higher performance in identification and verification of the signatures with different nationalities due to its independency of the shape and the structure of signatures. This is verified by testing the proposed system on a sample of 640 signature databases with different nationalities. Even the system structure of the proposed method is simple; its accuracy is equal or even greater than the similar systems. According to another experiment, it was shown that the accuracy of our proposed system is equal to and greater than the human accuracy in signature identification and signature verification respectively. This method is a hierarchical model inspired by the cortex structure of human's brain. The object recognition procedure in cortex employs a kind of hierarchical multi-resolution and -direction edge detection. In the proposed system, the weighted distance was used in nearest neighbor classifier. It is suggested to use the other powerful statistical pattern recognition method such as SVM in classification stage.

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