Classification of Offline Handwritten Signatures using Wavelets and a Pattern Recognition Neural Network

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ABSTRACT
The various studies conducted for classification of handwritten signatures of people have shown that the task is difficult because there is 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. The wavelet energy features corresponding to the approximation and detail along with the approximation and detail coefficients make the feature set. A pattern recognition neural network is designed which classifies the inputs based on the target classes.

General Terms
Classification, Offline Signatures, Genuine signature, Forgery

Keywords
Wavelets, Principal Component Analysis, Pattern Recognition Neural Network

1. INTRODUCTION
Hand written signatures are accepted means of a person's identification in almost all government, legal and commercial transactions. As a result, the signatures are highly vulnerable and are often forged and misused. It becomes necessary to correctly verify whether a signature is a genuine or a forgery.

There are two types of signature classification systems namely an Offline Signature Classification system and an Online Signature Classification system. Online approaches use a device or a digitizing surface to capture dynamic features like pressure, speed, direction which result in higher accuracies. Off-line verification deals with signatures that have been written on paper and digitized by scanning. Here because of the missing dynamic information the accuracy of the results is low.

1.1 Skilled Forgery
These are produced by professional imposters or persons who have expertise in copying the signature and this is the most difficult of all forgeries.

1.2 Casual Forgery
The forger imitates the signature in his own style without any knowledge of the spelling and does not have any prior experience. The imitation is possible because of observing the signature closely for a while.

1.3 Random Forgery
This is the simplest type of forgery where the forger uses the name of the victim in his own style to create a forgery known as the simple forgery or random forgery.

The usage of signatures for identification is well accepted form of identification in the society and a non-invasive method which does not annoy an individual being verified. However there are disadvantages like 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. The skilled forgeries pose the real difficulty in identification.

2. WAVELETS
A wavelet is a waveform which has an average value of zero and lasts for a limited duration and on an average its value is zero. Unlike sinusoids, a wavelet has a beginning and an end in contrast to the sinusoids which can extend from minus infinity to plus infinity. Wavelets are defined by the two functions namely a wavelet function $\psi(t)$ (the mother wavelet) and a scaling function $\phi(t)$ (called as the father wavelet) in the time domain.

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.

2.1 Continuous Wavelet Transform
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.

2.2 Discrete Wavelet Transform
Instead of analysing the signal at each scale and position, here the analysis is done at dyadic scales and positions which are powers of two resulting in an accurate analysis.

2.3 Daubechies Wavelet Transform

Daubechies wavelets are having an order *N* and hence it is written as dbN where N stands for the order of the wavelet. It is a regular wavelet, orthogonal, has compact support. This wavelet supports both the continuous wavelet transform and discrete wavelet transforms. Some of the properties of the Daubechies wavelet are as follows.

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

3. ARTIFICIAL NEURAL NETWORKS

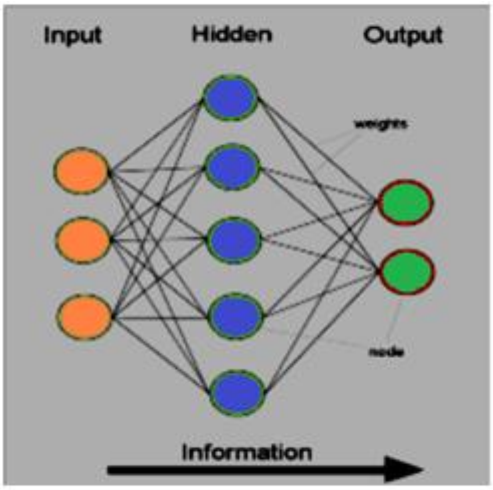

Figure 1: An Artificial neural Network

Neural networks are composed of simple elements which resemble the elements in biological nervous systems and they operate in parallel. The network function is largely determined by the connections between elements. One can train a neural network to perform a particular function by adjusting the values of the connections or weights between elements. Neural networks are usually adjusted, or trained, so that a particular input yields a specific target output. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. So, many such input/target pairs are needed to train a network but care has to be taken to avoid over-fitting of the data. In the various fields like pattern recognition, identification, classification, speech, vision, control systems, the neural networks are trained to perform complex functions.

3.1 Function of a Neural Network

Neural Networks incorporate the two fundamental components of biological neural nets. They are Neurons (nodes) and Synapses or weights. The output of a neuron is a function of the weighted sum of the inputs plus a bias. The function of the entire neural network is simply the computation of the outputs of all the neurons. The neural networks where information flows in one direction are called feed forward neural networks. The data is presented to input layer, then passed on to hidden Layer and finally passed to output layer. Information is distributed and Information passing is done in parallel. Data is presented to the network in the form of activations in the input layer and weight settings determine the behavior of a network. Though the training of the network can start with random weights and then weights can be adjusted based on the error between the output obtained and the desired output and this leads to learning (supervised). The back-propagation algorithm is a supervised learning method which is based on the minimizing the network error using the derivatives of the error function.

3.2 Hessian Matrix

The Hessian matrix values are the second derivatives of the performance index at the current values of the weights and biases. There is a Newton's method which often converges faster than conjugate gradient methods. Unfortunately, it is complex and expensive to compute the Hessian matrix for feed forward neural networks. There is a class of algorithms that is based on Newton's method, but it doesn't require calculation of second derivatives. These are called Quasi Newton (or secant) methods. They update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient.

3.3 Quasi Newton Method

Newton's method is an alternative to the conjugate gradient methods for fast optimization. The basic step of Newton's method is

$$(x_{k+1=}x_{k-}A^{-1}{}_k g_k)$$

Where $A^{-1}{}_k$ is the Hessian matrix.

4. RELATED WORK

A survey on offline signature recognition and verification schemes details the importance of the study of signatures and it's possible applications[1]. An offline signature verification system based on DWT and common features extraction has achieved good verification measure with low false acceptance rate of 1.56% and low average rate of 6.23% and false rejection rate of 10.9% [2]. A feed forward back-propagation neural network has been trained using novel diagonal and Statistical zone based features have reported a specificity of 89% and sensitivity of 95% [3]. A study using an artificial neural network based on the back-propagation algorithm has analyzed the various performance measures like the learning rate, FAR and FRR and reported a FRR of less than 0.1% and FAR of less than 0.2% [4]. An offline signature verification based on adaptive multi-resolution wavelet zero crossing and one-class-one network and using the zero crossings of curvature data of the projection is very effective in verification[5]. An intra-model score level fusion for offline signatures using the angular features verifies the signatures based on correlation and distance based metrics and has reported better FAR, FRR and EER compared to the existing algorithms[6]. Global features like slope, slope direction , density of thinned images, width to height ratio are used to train a feed forward neural network using error back propagation is used for recognition of signatures[7]. An online signature verifier based on self-organizing feature maps used the fast wavelet transforms for feature extraction [8]. An offline signature recognition using modular neural network and fuzzy reference system uses separate modules with features from edge detection, curvelet transform, Hough transform and combines the outputs form all these modules has achieved an accuracy of 96.6%[9].

A Neural network based offline signature verification uses global features like image area, pure width and height, centers of signatures and Eigen values[10]. Offline signature verification has been done based on grey level information using text features[11]. Online handwritten signature verification system wherein discrete wavelet transform (DWT) is used for features extraction and a feed forward back propagation error neural network is used for recognition. Pen position data (x and y positions) of points of the signature are extracted and then pen-movement angles are derived from pen position data. To reduce variations in pen-position and pen-movement angles dimensionality, data are normalized and resampled. Both the pen-position and pen-movement angle features are then associated for obtaining the decision about the verification of signatures[12]. A DWT based Off-line Signature Verification system using Angular Features (DOSVAF) use four bands form the DWT. The approximation band is skeletonized. The angular features are obtained by dividing the signature image into number of blocks and are used for comparison. The values of FAR and FRR measured at optimal threshold are said to be better compared to that of existing methods[13].

An offline signature verification system with a SVM classifier uses Radon Transform, Ridgelet Transform and PCR5 combination rule based on the generalized belief functions of Dezert-Smarandache theory. This system combines the normalized SVM outputs and an estimation technique based on the dissonant model of Appriou. Decision making is done through likelihood ratio. The results on the CEDAR database show improved verification accuracy compared to individual SVM classifiers[14]. An offline signature verification uses Discrete Wavelet Transform for feature extraction. Wavelet energy values are the features and a Wavelet Neural Network is used as a classifier to solve the problem. A comparative study of the proposed system with other off-line handwritten signature recognition systems is illustrated[15]. A signature identification system uses the rotated complex wavelet filters (RCWF) and dual tree complex wavelet transform(DTCWT) together to extract the features which represent the information in twelve different directions. Canberra distance measure is used for classification. The results of this method are superior to DWT[16]. An offline handwritten signature identification and verification uses a feature extraction method based on Gabor wavelet transform and Gabor wavelet coefficients pertaining to different frequencies and directions are fed to a shortest weighted distance based classifier. The CCR and EER of the system 100% and 15% respectively on a Persian signature database[17]. A signature verification system uses both static and dynamic features of signature data and 1D-log Gabor wavelet is used for analyzing the textural features and Euler numbers are used for analyzing the topological features of the signature respectively. The results from three feature sets are combined by a multi-classifier decision algorithm and an accuracy of 98.18% is attained[18]. An Ensemble Classifier Approach which is a combining approach to improve the accuracy of the simple classifiers is used and Gabor wavelets are used to compute the Gabor coefficients in different scales and directions. Statistical approaches are used to extract three different feature sets and a nearest neighbor classifier classifies each feature set by an adaptive method. The output of the three simple classifiers are combined since each classifier works on different feature set and adaptive thresholds. Experiments are done on Persian and South African signature datasets and produce the lowest error rate in comparison with other methods[19]. The transform domain features from four sub bands are extracted signatures as a result of a Discrete Wavelet Transform (DWT) and some global features are extracted which form the spatial domain features. Both the transform domain and spatial domain features are combined to obtain a final set of features. The test signature features are compared with data base signature features vector using correlation technique. The values of FAR and EER are low when compared to existing algorithms[20]. An offline signature recognition system employs three different kinds of feature extractors, wavelet, curvelet and contourlet transform. The curvature and orientation of a signature image make the feature set and a Support vector machine (SVM) is used for evaluating the performance of the three feature extractors. The comparison of the three transforms showed that the contourlet transform can extract better features among them [21].

5. PROPOSED SYSTEM

In this paper, we have designed an Off-line Signature classification system which uses the Discrete Daubechies Wavelet Transform to extract wavelet coefficients in three directions namely horizontal, vertical, diagonal and a pattern recognition neural network classifier is designed where the training algorithm is a Quasi-Newton algorithm and the classification is done. The signature images from Standard GPDS database have been preprocessed and then Daubechies wavelet transform is used to decompose the signature images up-to the maximum possible level. The wavelet energy of the approximation, the detail in the three directions and the principal component values of approximation and detail coefficients form the feature vector which are used in training the pattern recognition neural network and the classification is done.

5.1 Preprocessing of Images

The database consists of signatures belonging to 640 persons. For each person, five genuine signatures and five forgery signatures are used for training. 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 images. After resizing or normalizing, the images have been thinned in order to eliminate the effect of using different types of pens.

5.2 Feature Extraction

The five preprocessed images of the genuine signatures and five forgeries for a signer are decomposed by db4 wavelet transform up to the maximum level possible. The approximation and detail coefficients obtained are very large in number and hence using Principal Component analysis, the first ten principal components are chosen. Also the wavelet energy corresponding to both approximation and the details in three directions namely horizontal, vertical and diagonal are computed. The energy features and the ten principal components of each of the approximation and details coefficients form the feature vector and are used to train a pattern recognition neural network.

5.3 Pattern Recognition Neural Network

Patten recognition neural networks are feed forward networks and they can be trained to classify inputs according to target classes. The target data for pattern recognition neural network should consist of vectors of all zero values except for a 1 in element *i* where *i* is the class they are representing. We have designed the network in Matlab software. There are three important parameters taken by the pattern recognition neural network. They are 1) The row vector of one or more hidden layer sizes (default=10). 2) Training Function – trainbfg (a quasi-newton algorithm). 3) performance function - we have used the cross entropy for measuring the performance. In the cross entropy method it is of interest to model the probabilities of class memberships conditioned on input data. i.e *p(i/x) where i=1,2…c* and determine the unknown model parameters via the maximum likelihood estimation.

5.4 Classification Results

There are signatures belonging to 640 people in the GPDS database. There are 24 genuine signatures and 30 forgeries available for each person. Therefore the total number of signatures in the database are 34,650. Five genuine signatures and five forgery signatures from each person are used for training the neural network. For each person, there are totally 44 features extracted. There are four wavelet energy feature values for both approximation and details. There are ten principal component values each for approximation, horizontal, diagonal and vertical wavelet coefficients. Genuine signatures are classified properly with an accuracy of 98%. But the forgery signatures are classified only 75% of the times properly. Method needs improvement for forgery signatures. The results have been tabulated in table 1. The false acceptance rate is 25% and the false rejection rate is 2%.

5.5 Conclusion

The proposed system has been studied on a large database of 640 signers with 34650 signatures totally available in the database. Since the false acceptance rate is quite high, some modification in the form of increasing the number of hidden layers and their nodes along with the more efficient training algorithms are highly desirable and have the potential for better accuracies.

6. ACKNOWLEDGEMENTS

I sincerely thank Ravindra S Hegadi, associate professor, School of Computational Sciences, Solapur University, Solapur, Maharashtra for his valuable guidance for all my research endeavours.

Table 1: Results Obtained for GPDS Signature Database

Number of persons:640 Number of Genuine signatures per person:24 Number of Forgeries per person:30 Total No of Signatures=34560 (640 *(24+30))			
Number of genuine signatures used for training:5			
Number of forgeries used for training :5			
Number of genuine signatures used for testing	Number of forgeries used for testing	Number of genuine signatures classified correctly	Number of forgeries classified correctly
12,160 (19*640)	16,000 (25*640)	11,196	8397
FAR	0.25%		
FRR	0.02%		

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