

Efficient Fusion based Directional and Textural features for Signature Verification

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Abstract— *Biometric signature verification, nowadays an important technique to recognize human identity. The accuracy of signature verification has lot of scope for improvement. In this paper, we propose an offline signature verification using fusion of Directional and Textural features. The Image is preprocessed and divided into sub-bands by applying DWT. The Directional features- Gradient, Coherence, Orientation and Textural features- correlation, energy and homogeneity are computed from the sub-bands and concatenated to form feature vector. The Feed Forward ANN tool in MATLAB is used for classification and verification. The results of False Rejection Rate (FAR), False Acceptance Rate (FAR) and Total Success Rate (TSR) are obtained for GPDS-960 database. A total of 204 images are used for training and testing. It is observed that the values of FRR, FAR and TSR are improved compared to the existing algorithms.*

Index terms— ANN, Biometric, Coherence, DWT, Textural features.

I. INTRODUCTION

Security is a big problem in this rapidly growing world. Unauthorized usage of bank accounts, legal documents and personal identification systems has been on the rising side. Hence it is necessary to incorporate a suitable security system to avoid these. Current security practices involve the use of pin number, password and access card. These tokens are not very reliable as they can be lost or forgotten and further restrictions do not exist which can prevent an unauthorized person using them in automatic verification machine. On the other hand, Biometrics measures cannot be easily duplicated or cannot be stolen, hence are more secure. Computer technologies today can easily be accommodated to carry out common biometric tasks. Biometrics is most commonly used approach for personal identification and verification. Hence several Biometric techniques have been proposed in last decade based on *Physiological* and *Behavioral* characteristics. *Physiological* biometrics deals with features like finger print, iris, retina and hand geometry which are stable for a long time. *Behavioral* biometrics measure the user action such as speech, signature and gait which are affected by health, age and physiological factors. The Signature is one of the *behavioral* biometric and is accepted socially and legally to verify the personal identity for usage of cheques, credit cards and legal documents.

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The goal of Automatic signature verification system is to verify the identity of individual based on the analysis of his or her signature through a process that discriminates a genuine signature from a forgery.

Signature Verification is of two types such as online and offline verification. Online verification refers to signatures which are captured during writing process and provides dynamic information like writing speed and pressure. Offline verification refers to signature images acquired by a scanner or digital camera. Offline signature verification systems are more difficult than online system because the dynamic information like duration, time ordering, number of strokes and direction of writing are lost. But the main advantage of Off-Line signature verification is that it does not require any special devices when the signature is acquired.

II. RELATED WORK

Saad Mamoun Abdel Rhman Ahmed [1] proposed offline signature verification that can be carried out using combination of Geometric and Grid feature. In grid method four points are marked in the directions of left, right, up and down. Highest and lowest points in the vertical direction are joined. Similarly, rightmost and leftmost points are joined and the features are extracted from the image thus formed. The grid method uses the grid features from the core of signature Image. Vu Nguyen and Michael Blumenstein [2] proposed signature verification system using grid based feature extraction technique which uses directional information extracted from signature contour which is called *the chain code histogram*. The algorithm uses 2D Gaussian filter on the matrices containing the chain code histogram. Srikanta Pal et al., [3] proposed a technique called bi-script offline signature identification system which used features such as under sampled bit map, modified chain code direction features and gradient features computed from background and foreground components. Support vector machine (SVM) and nearest neighbourhood (NN) techniques are used as classifiers in this system. A high value of accuracy was obtained. Dakshina Ranjan Kisku et al., [4] proposed a system which uses three different classifiers namely Gaussian empirical rule, Mahalanobis and Euclidian distance metrics. Initially, geometric global and local features are extracted from signature image. Further, a novel feature extraction technique is applied to signature image for extraction of orientation features. This paper reports a weighted fusion of multiple classifiers for offline verification. B.H.Shekar and R.K.Bharathi [5] proposed a model which has a pre-processing stage and an eigen signature construction stage.

In the pre-processing stage scanned signature is converted to a shape form and from this the feature vectors are extracted using eigen signature construction. Konstantinos Tselios et al., [6] proposed a feature extraction method for offline system. It is based on relative pixel distribution over a pre-determined two and three-step path along the signature trials. The procedure includes estimating transition probability of the signature stroke, arc and angles. Signature is partitioned with respect to its centre of gravity and applied to two-step part of the algorithm while three-step utilizes entire image.

Srikanta pal et al., [7] proposed a verification system involving Bangla signature as their style which is different from the western language. The proposed technique uses Gaussian method for feature extraction and SVM as classifier. Abd Fatah Wahab et al., [8] considered signatures as fuzzy data and proposed an interpolation method using Fuzzy Interpolation Rational Bezier Curves (FIRCBC) which uses fuzzy set theory as basis for models of uncertain data.

Muhammed Reza Pourshahabi et al., [9] presented offline signature identification and verification using Contourlet Transform (CT). Noise removal was performed in the pre-processing stage followed by normalization. The Contourlet Transform was applied to compute the contourlet coefficients and feature vector was formed. Classification was performed using the Euclidean distance classifier. Md. AsrafuHaque, et al., [10] proposed a method for off-line signature verification that depends on structural property of blocks in image. The image is divided into several blocks which are represented by a set of features like number of pixels in each block, block-centre and distance from the image centre. Each type of feature has a different impact for assigning some weightage to a block. Experimental result shows that the method eliminates random and simple forgeries and also reduces skilled forgery to a great extent. Luana Batista et al., [11] proposed a system which uses a two-stage off-line signature verification system based on dissimilarity representation. In the first stage, a set of discrete left-to-right HMMs trained with different number of states and codebook sizes is used to measure similarity values that populate new feature vectors. Then, these vectors are input to the second stage, which provides the final classification.

Nassim Abbas and YoucefChibani [12] proposed a signature verification system based on decision combination of off-line signatures. The proposed system has basically three modules: Radon Transform-SVM, Ridgelet Transform-SVM and PCR5 combination rule based on the generalized belief functions of Dezert-Smarandache theory. Combining the normalized SVM outputs and using an estimation technique based on the dissonant model of Appriou, belief assignments can be computed. Likelihood ratio is used for decision making. Vu Nguyen and Michael Blumenstein [13] proposed a paper that investigates on the performance of a small feature set consisting of 33 feature values. In their experiments using Support Vector Machines (SVMs), an average error rate (AER) of 16.80% was obtained together with a low false acceptance rate (FAR) for random forgeries of 0.19%. The significant reduction of the error rate was obtained when the proposed global features were employed, which demonstrates their astonishingly high discriminant power.

Mustafa BerkayYilmaz et al., [14] proposed a model of verification system based on a signature local histogram feature. The signature is divided into zones using polar and Cartesian co-ordinate method. From each zone histogram of oriented gradient (HOG) and histogram of local binary pattern (LBP) are calculated. The global SVM is used as classifier. Juan Hu and YoubinChen [15] proposed a method for writer independent offline signature verification based on grey level feature extraction and Real Adaboost algorithm for their implementation. Initially both global and local feature are developed and from that a vector is developed for which robust algorithm is applied. Ji Jun-wen et al., [16] presented a new method for offline Chinese signature verification. This approach is based on feature extraction of every segment segmented from the image. Every segment is represented by a set of seven features because each feature has different impact for verification on each type weighting factor is very important for the similarity computation. Elaheh Soleymanpour et al., [17] proposed Contourlet Transform (CT) based signature verification which uses CT coefficients computed in specified direction and scale. In the feature extraction stage, coefficients extracted are fed as feature vectors to the SVM classifiers which determine the class to which the input image belongs. Soulo Henrique Leoncico de Medeiros Napoles and CleberZanchettin [18] proposed a radial basis function optimized by Differential Evaluation Algorithm as features which discriminates between genuine and forged person. GPDS300 used for database.

J P Swanepoel and J Coetzer [19] presented a two-novel offline signature verification system developed by an assembly of weight-based classifiers. The flexible grid-based feature extraction technique was proposed. Dolfing's dataset signature database was used. IA Ismail et al., [20] presented a method for Offline recognition and verification of signatures using Principal components analysis. The Principal components analysis is evaluated for the extracted feature. The K nearest-neighbours are used in the recognition process and Neural Network classifier is used in the verification process. Assia Hamadene et al., [21] proposed a method for Off-line Handwritten signature verification which uses Contourlet transform and Co-occurrence matrix. The contour segment direction of the handwritten signature is captured using contourlet transform and the number of directions is described by co-occurrence matrix. Vahid Malekian et al., [22] used signature envelope and adaptive density partitioning to extract the features of offline signature. The four features namely aspect ratio, horizontal to diagonal length ratio, the slope of the line joining the centre of gravity and geometric centre were extracted. Two more features such as envelop signals and signature density around the centre of gravity were also calculated. All the features were concatenated to form the feature vector. The matching and verification was performed using multi layer perceptron neural network.

III. PROPOSED SYSTEM

The signature samples from GPDS 960 Database are used for training and testing. In training signature samples are preprocessed to filter unwanted noise and features extracted are stored.

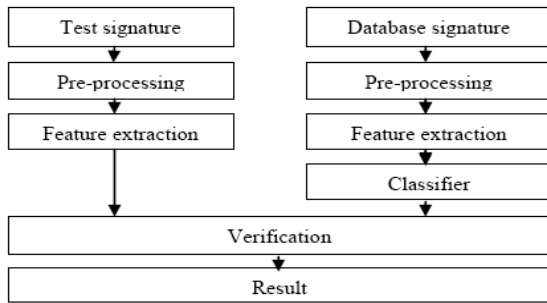


Fig 1. Flow Diagram

In testing, the preprocessed and extracted features are used for classification.

A. Pre-processing

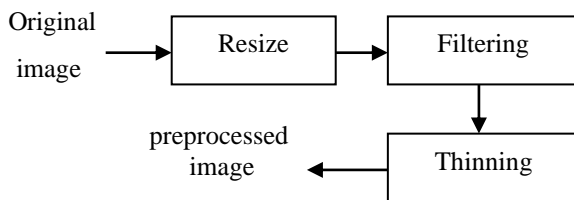


Fig. 1. Pre-processing.

In Pre-processing stage the original image is preprocessed with filtering and morphological operations to obtain accuracy.

i) *Resizing*: The images are resized to a common dimension matrix of 256 x 256.

ii) *Filtering*: Each captured image may have various interferences, noises degrading the quality. At the same time, it makes the analysis a big difficulty. Therefore, we need to suppress unwanted noise to improve image quality. The Gaussian low pass filter was used and the response in frequency domain is expressed as,

The GLPF with cut-off frequency D_0 is defined as:

$$H(u, v) = e^{-D^2(u,v)/2D_0^2} \quad (1)$$

iii) *Thinning*: It is a morphological processing. Since signature might be signed using pens of different thicknesses, thinning is carried which reduces the thickness of the image to one pixel (i.e., extra unwanted pixels are deleted). The two principal morphological operations are dilation and erosion. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded. The `bwmorph-thin` function is used in MATLAB to perform thinning.

B. Feature Extraction

The second stage is called feature extraction in which unique features of Directional and Textural are extracted. Directional features include gradient, coherence and dominant local orientation and Textural features include correlation, energy, homogeneity and contrast. The extracted features are fused to form a single array which is stored in the database.

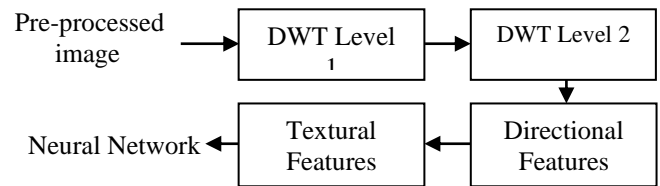
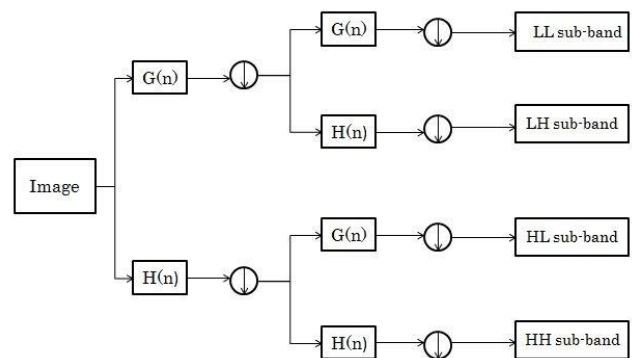


Fig. 2. Feature Extraction.

The array can be accessed in future for comparison with a test signature. Feature extraction is done for all images-genuine, forged and test which are used during the verification process.

1) *Two-level DWT*: DWT is the time-frequency representation of an image and is mainly advantageous over other transforms such as fourier transforms because of their capability to transform the image in both time and frequency domain by using shifting and scaling operations. DWT is used as an image compression technique, mainly used to obtain detailed information about the image and meet the time constraints in real time as the computational time required for DWT is very much less compared to other transforms. The size of original image (N x N) at the first level of applying DWT, convolve the rows of the image with $g(n)$ (transfer function of a LPF) and $h(n)$ (transfer function of a HPF) and down sample columns by 2. The columns of each of $N/2 \times N$ data are then convolved with $h(n)$ and $g(n)$ and the alternate rows are discarded. The result of entire operation gives four $N/2 \times N/2$ images. Similarly, after applying second-level of DWT, image size obtained will be $N/4 \times N/4$.



G(n):low pass decomposition filter
H(n):high pass decomposition filter
⊘ : downsampler

Fig. 4.DWT Block Diagram.

Applying DWT decomposes the image into 4 sub-bands namely LL, LH, HL, HH where LL provides complete information about the image, LH provides horizontal information about the image, HL provides vertical information about the image and HH provides diagonal information about the image.

The Haar wavelet's mother wavelet function $\psi(t)$, which was used to calculate DWT, can be described using equation 2 and equation 3.



$$\psi(t) = \begin{cases} 1 & 1 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Its scaling function $\phi(t)$ can be described as

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

2) Directional features:

i) **Gradient:** It signifies the directional change in the intensity or color in an image. The gradient [23] and corresponding angle at the position (m,n) are given in equation 4 and equation 5 respectively,

$$G_{mn} = M * (|G_{mn}^x| + |G_{mn}^y|) \quad (4)$$

$$\theta_{mn} = \tan^{-1}(G_{mn}^x/G_{mn}^y) \quad (5)$$

G_{mn}^x and G_{mn}^y represent the components of G_{mn} in horizontal and vertical directions respectively.

ii) **Coherence:** Coherence indicates how similar two given pixels are over the whole image. In other words, it is a measure of correlation [23].

$$\delta_{mn} = \frac{\sum G_{ij} \cos(\theta_{mn} - \theta_{ij})}{\sum G_{ij}} \quad (6)$$

Where, $i= 1$ to 5 and $j=1$ to 5 (because the size of the window is 5 x 5).

Coherence is calculated from gradient determined in the previous step.

iii) **Dominant local orientation:** It provides directional information about the image. Dominant local orientation points in the direction of gradient at that point. Dominant local orientation is calculated from the gradient and coherence [23] as given in equation 7,

$$\theta = \frac{1}{2} \tan^{-1} \frac{\sum_{m=1}^N \sum_{n=1}^N \delta_{mn}^2 \sin 2\theta_{mn}}{\sum_{m=1}^N \sum_{n=1}^N \delta_{mn}^2 \cos 2\theta_{mn}} + \frac{\pi}{2} \quad (7)$$

Where, N is 8. Thus, each 8x8 size window represents one directional information.

3. Textural features:

i) **Correlation:** It is a measure of how correlated (similar) a pixel is to its neighbor over the whole image

$$\text{correlation} = \sum_{i=1}^N \sum_{j=1}^N \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \quad (8)$$

Where, μ = mean, σ = standard deviation.

ii) **Homogeneity:** It measures the closeness of the distribution of elements in the gray-level co-occurrence-matrix (GLCM) to the GLCM diagonal. The range obtained for GLCM is [0 1].

$$\text{Homogeneity} = \sum_{i=1}^N \sum_{j=1}^N P(i,j)/(1 + (i - j)) \quad (9)$$

iii) **Energy:** Energy is used to describe a measure of 'information' when formulating an operation Energy corresponds to the mean squared value of the image (typically measured with respect to the global mean value). It is calculated using equation 10.

$$\text{Energy} = \sum_{i=1}^N \sum_{j=1}^N P(i,j)^2 \quad (10)$$

iv) **Contrast:** It is a measure of the intensity difference between a pixel and its neighbor over the whole image. Hence contrast is zero for a constant image. Mathematically it is given by the equation 11.

$$\text{Contrast} = \sum_{i=1}^N \sum_{j=1}^N (|i - j|)^2 P(i,j) \quad (11)$$

C. Verification

This stage involves verification of the signature i.e., a test signature is taken and determined whether it is a genuine or forged. Even though other classifiers such as Euclidian distance could be used for authentication of signature images, artificial neural networks are used since they are designed interpreting the intelligence of a human brain.

A neural network is very similar to a human brain. It first learns from various examples provided in the form of training objects-this process is called training. Once it is trained, it can be used to check whether a test object is similar to the trained object. Feed forward backpropagation NN was chosen since it is the best which suits this type of comparison, as the error is backpropagated and reiterated every time. Artificial neural networks is trained using the features of set of genuine signatures followed by the features of set of forged signatures which enables the ANN to identify an image whether genuine or forged. During training, the set of features obtained in the feature extraction stage are used. ANN uses these features to adjust its weights and biases and prepare the network for verification. When the test images are provided, the ANN authenticates whether the signature is genuine or forged.

IV. RESULTS AND DISCUSSIONS

Experiment is conducted on 204 images of selected 17 individuals from GPDS-960 database. Each person's database consists of 18 genuine signatures and 18 forged signatures and

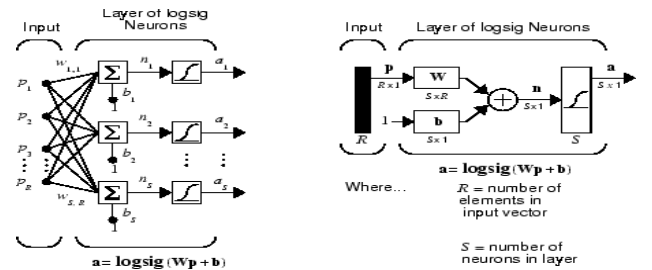


Fig. 5. Feed forward backpropagation neural network structure.

12 test samples which consist of 6 genuine and 6 forged signatures. Verification was performed using Feed Forward Back propagation ANN tool in MATLAB.

Design of neural network:

- Number of neurons of input layer = Image features=314.
- Number of hidden layers = 2 (Signatures are complex patterns and hence only one hidden layer may not be sufficient).
- Goal was set to 10^{-6} (in order to minimize the error between the target and trained sample this value must be as low as possible).
- Epochs = 1000 (It indicates the number of iterations taken to compute the result before getting the final value).

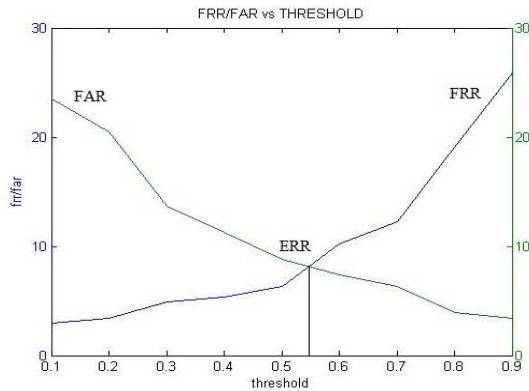


Fig. 6. Graph of FAR/FRR vs. Threshold.

The experimental results are shown in Figure 6. It can be seen that as FRR increases the FAR decreases for different values of thresholds and better results were obtained at the threshold value of 0.55 which corresponds to ERR (equal error rate). Hence considering a threshold value of 0.5 will achieve better result.

Table I gives the values of False Acceptance Rate (FAR), False Rejection Rate (FRR) and Total Success Rate (TSR) obtained in our algorithm which is tested on GPDS-960 database. FAR and FRR are calculated for 204 images of selected 17 individuals using GPDS-960 database.

TABLE I. FAR/FRR AND TSR CALCULATION.

Parameter	Percentage
FAR	9.34%
FRR	4.9%
TSR	86.3%

The percentage values of FRR and FAR for proposed and existing algorithms are given in Table II. It is observed that the percentage of FRR is improved in the proposed method compared to the existing methods as transform domain features are more precise than spatial domain features.

TABLE II. FRR and FAR values for existing algorithms and proposed algorithm.

Authors	%FRR	%FAR
M Nasiri and A Javaheri [24]	10.3	8.1
K V Laksmi and Seema Nayak [25]	8	12
Proposed Method	4.9	9.34

Table II shows that the proposed approach has better FAR and FRR for standard database of ‘GPDS-960’ compared to the references mentioned above.

V. CONCLUSION

In this paper offline signature verification based on Transform domain feature and Textural features is presented. The necessary preprocessing techniques such as resizing, filtering and thinning using morphological process is applied on the signatures to improve the matching accuracy. The Feed Forward Back Propagation Neural Network is used for classification and tested for 204 samples from GPDS-960 database with accuracy 86.3%. The FAR and FRR are computed for different threshold values. The EER where FAR and FRR is minimum is achieved for threshold of 0.5. The Results of FAR and FRR for the proposed technique shows minimum compared to existing algorithms.

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