Concatenation of Spatial and Transformation Features for Off-Line signature Identification

Ravi J, K B Raja

Abstract- Off- Line signature is a behavioral biometric trait and is widely accepted for personal and document authentication. In this paper we propose Concatenation of Spatial and Transformation Features for Off-Line signature Identification (CSTSI) method to distinguish genuine signature form skilled forgery signatures. The Discrete Wavelet Transform (DWT) is applied on signature to derive transform domain features from all the four sub bands. The signature is preprocessed and global features are extracted leads to spatial domain features. The transform domain and spatial domain features are concatenated to obtain final set of features. The test signature features are compared with data base signature features vector using correlation technique. It is observed that the values of FAR and EER are low in the case of proposed algorithm compare to existing algorithm. As FAR value is less, that indicates skilled forgery is successfully rejects.

Key Words: Signature. Global Features, DWT, Correlation, Fusion

I. INTRODUCTION

Biometric security system is a highly important and becoming a prime issue for ensuring the security and surveillance compared to electronics based security. Biometric recognition system is an automatic recognition of individuals based on a feature vector(s) derived from their physiological and/or behavioral traits. The physiological traits are fingerprint, face, hand geometry, vein patterns, retina and iris etc., are almost unchanged throughout person's life. The behavioral traits are speech, gait, key stroke and hand written signature etc., are changes with environment, mood and age. The biometric method of verification/ identification is extensively used in number of applications for authentication of an individual or document verification in day to day routine activities in airports, bank checks, credit card transactions, certificates, contracts and bonds etc. The biometric system is more secure because it cannot be breached easily, stolen, borrowed forgotten or shared compared to traditional methods such as Personal Identification Number (PIN), passwords, security questions, ID badges and smart cards etc.

The signature being a behavioral biometric trait is widely used and well accepted socially and legally for document authentication, authorization and personal identification. Automated recognition of handwritten signatures is very important because it is very difficult to distinguish genuine signatures from simulated forgeries signatures on the basis of visual evaluation. This led to computer recognition of handwritten signatures i.e. more reliable and competent. The signature verification system can be divided into two main classes namely, (i) *Dynamic or On-line verification method:* The signature is captured during the writing process on a digitizing tablet and stored to a computer to evaluate the dynamic information like writing speed, pressure points, strokes, velocity, acceleration and distance travelled etc., to identify a person and (ii) *Static or Off-line verification method:* The signature is captured once after the writing process is over on an ordinary piece of writing paper and scanned into a computer system, the information like width, height, aspect ratio, center of gravity etc., are measured to identify a person. The signature forgeries are classified into three types of forgery (i) *Simple forgery:* The forger makes no attempt to simulate or trace a genuine signature and does not have any prior experience. (ii) *Random forgery:* The forger uses his/her own signature as a forgery, iii) *Skilled forgery*: The forger practices and tries to imitate as closely as possible of the signature to be forged. The problem of signature verification is difficult for skilled forgeries compared with simple and random forgeries.

The biometric identification system using information from single feature extraction method has some limitations in terms of Total Success Rate (TSR), False Rejection Rate (FRR) and False Acceptance Rate (FAR). These limitations can be eliminated by fusing two or more features to ensure an improved performance. The three possible levels of biometrics fusion are: (i) *at feature extraction level:* The different features biometric parameter are combined to generate new set of features, (ii) *at matching score level:* The matching scores are obtained from different features biometric parameter and are fused by different techniques and (iii) *at decision level:* The resulting features from multiple biometric data are fused individually to classify either accept or reject.

Contribution- In this paper CSTSI algorithm is proposed to reject forged signatures successfully. The spatial domain global features and transform domain DWT features are derived and concatenated to obtain final features set. The correlation technique is used to compare features of test image with data base images.

Organization- The paper is organized as follows. Section II presents related work. Section III explains the proposed model. Section IV explains the algorithm. Section V gives the results and performance analysis and Section VI gives the conclusion.

II. LITERATURE SURVEY

Guangyu Zhu et al., [1] proposed an algorithm for signature detection and matching.

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Multi scale approach is applied for image segmentation and detection by capturing the structural curvature of 2D contour fragments. Secondly signature retrieval is carried out by setting of translation, scale, and rotation invariant non rigid shape matching. Luana Batista et al., [2] developed off-line signature verification system using hybrid generative–discriminative ensembles of classifiers. Generative stage is designed using multiple discrete left-to-rights Hidden Markov Models. Discriminative stage is designed using HMM likelihoods by measuring each signature and assembled in to feature vector. Verification is carried out using K-nearest-oracles algorithm and reduces the overall error rate. Kai Huang and Hong Yan [3] developed off-line signature verification using structural feature. Statistical models are constructed for both pixel distribution and structural layout description. Geometric handwriting features and directional frontier feature are extracted. The statistical verification algorithm is applied by comparing the detailed structural correlation between the input and reference signatures to detect skilled forgeries. Madasu Hanmandlu et al., [4] have developed off-line signature verification and forgery detection using fuzzy modeling technique using angle features extracted from box approach corresponds to a fuzzy set. Structural parameters are generated by fuzzified by an exponential membership function. The structural parameters taken into account of possible variations due to handwriting styles and reflect moods Eshwarappa and Mrityunjaya V Latte [5] proposed a method for person authentication system using speech and signature features. Signature system is developed by using Vertical Projection Profile, Horizontal Projection Profile and Discrete Cosine Transform is applied to generate signature features.

Vahid Kiani et al., [6] develop a technique offline signature verification using local radon transform and support vector machines. SVM is used as classifier. Radon transform locally is used for line segments detection and feature extraction because robustness to noise, size invariance and shift invariance. Proposed method gives better results. Farhad Shamsfakhr [7] has proposed analysis of intersection paths for accurate recognition of the electronic signature. Features are extracted by considering array, stack, list and determination of the sensitivity level for recognizing the accuracy of the signature by setting an error percentage for the size and recognition of the shape. The recognition test was performed for 15 signature samples of 150 types of signatures. Vargas et al., [8] have proposed technique Off-line signature verification based on grey level information using texture features for MCYT-75 and GPDS-100 database. The method start with background removal, histogram is applied to remove the influence of different writing ink pens used by signers. Statistical texture features are extracted by measuring global image level and the grey level variations in the image. To train an SVM model, genuine and random forgeries are used. Mohamad Hoseyn Sigari et al., [9] developed a Signature Identification and Verification using Multi-Resolution Gabor Wavelet for four signature dataset with different nationalities including Iranian, Turkish, South African and Spanish signatures. Pre-processing is carried out for noise reduction and signature image normalization by size and rotation, a virtual grid is placed on the signature image. Gabor wavelet is applied to extract feature coefficients with different frequencies and directions on each points of this grid. The shortest weighted distance is used as the classifier based on the distribution of instances in each of signature.

Hemanta Saikia and Kanak Chandra Sarma [10] discussed different techniques and issues in off-line signature verification system for different forgeries like random, simple and skilled forgeries. Different techniques are discussed to extract global and local and geometric features to improve the performance of the system. Piyush Shanker and Rajagopalan [11] proposed off-line signature verification using Dynamic Time Warping technique. The features are extracted by vertical projection of signature images finally comparing the reference and extracted features using elastic matching. Ashwini Pansare and Shalini Bhatia [12] developed Signature Verification method using Neural Network.

The geometric features are extracted after preprocessing, and then the extracted features are used to train a neural network using error back propagation training algorithm. In verification stage the extracted features of test signature to a trained neural network to check genuine or forged signature. Miguel A Ferrer et al., [13] developed offline signature verification system. Gray level features are extracted using Histograms of local binary, local directional and local derivative patterns using nearest neighbor and SVM classifiers under different conditions like changing the number of training signatures, multiple signing sessions, database with different inks, increasing the number of signers and combining different features at score level. Mehmet Sabih Aksoy and Hassan Mathkour [14] proposed off-line signature verification using 3-ext inductive learning algorithm. Template matching technique is used for feature extraction and 15 of 3 × 3 masks were used to represent a signature. Each signature is presented by the frequencies of the masks. The system was tested for 144 signatures of nine different persons. Meenakshi S Arya and Vandana S Inamdar [15] have proposed Various Off-line Hand Written Signature Verification approaches like Template Matching Neural networks, Hidden Markov models, Statistical approach, Structural or syntactic, Wavelet- based approach are discussed.

III. MODEL

In this section the definitions of performance parameters and the proposed model is discussed.

A. Definitions:

(i) False Rejection Rate (FRR): It is the measure of biometric system performance that incorrectly rejects an access attempt by an authorized user and is given in Equation 1.

$$FRR = \frac{Number\ of\ Falsely\ rejected\ images}{Total\ number\ of\ persons\ in\ the\ databese} \quad (1)$$

(ii) False Acceptance Rate (FAR): It is the measure of biometric system performance that incorrectly accepts an access attempt by an unauthorized user and is given in Equation 2.

$$FAR = \frac{Number\ of\ Falsely\ accepted\ images}{Total\ number\ of\ persons\ out\ of\ database} \quad (2)$$

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(iii) Total Success Rate (TSR): is the probability that different images of the same person are matched correctly and is given in Equation 3.

$$TSR = \frac{Number of\ Correct Persons\ Matched}{Total number of\ Persons\ in\ the\ Database} \qquad (3)$$

(vi) Equal Error Rate (EER): the rates at which both FRR and FAR errors are equal.

$$EER = FAR = FRR \qquad (4)$$

B. Proposed CSTSI Model

In the proposed model, the spatial and transform domain techniques are used to generate features of signature image to identify a person more effectively. The proposed block diagram is as shown in the Figure.1.

(i) Signature database:

The Grupo de Procesado Digital de Senales (GPDS) database is considered and has 160 signers with 300 dpi resolution and 6.3cm X 4.5cm size is as shown in Figure 2. The database consists of 24 genuine signatures and 24 forgery signatures of each signer. The data base is created by considering first 30 signers out of 160 signers and first 20 signature samples are considered out of 24 samples of each signers for training which leads to 600 signature images in the database and the twenty second image of each signer is considered as test image to compute FRR and TSR.

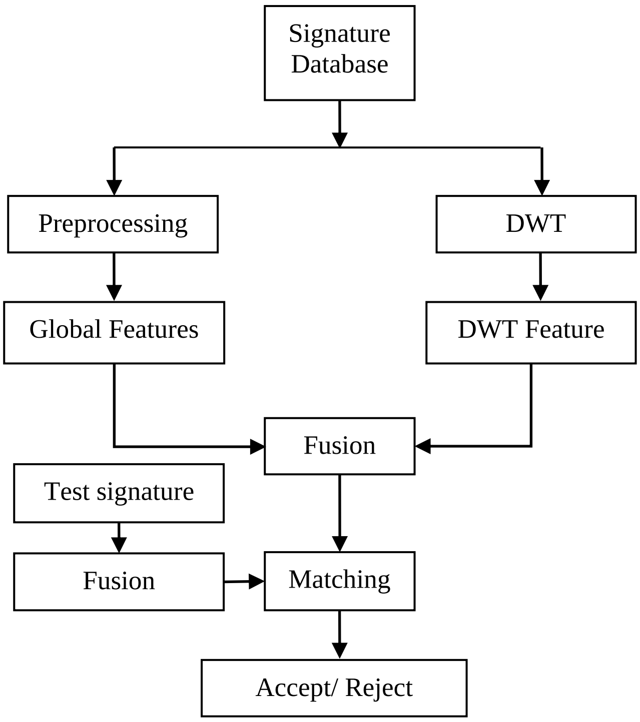

Fig.1.The block diagram of CSTSI

(ii) Signature preprocessing

The Robert edge detection is applied on signature image to convert into edges. The Gaussian filter is used to remove noise in the signature image. The morphological operation such as dilation and erosion are used to fill up the gaps in the signature and remove extra pixels on signature respectively to keep signature without any breaks and converted into one pixel width. The original signature and preprocessed signature is as shown in Figure 3. The exact signature area is calculated by scanning the pixel from first row and first column and continues to the next column to the right side until it locates the black pixel in a column. Same scanning process is carried from left to right, top to bottom and bottom to top to locate the black pixel in an image.

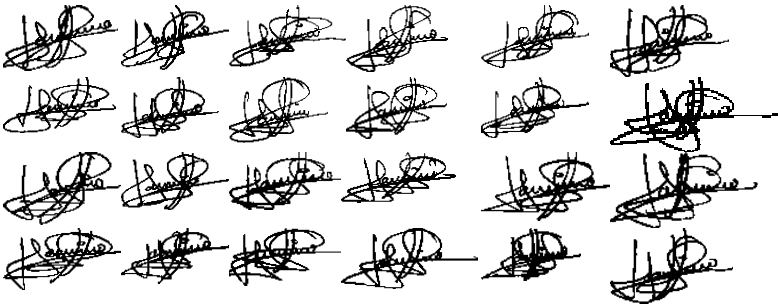

Fig.2. GPDS Database

(a) (b)

Fig.3. (a) Original image (b) Thinned image

(iii) Feature Extraction:

(a) Transform Domain Features:

The DWT is applied on signature to derive the DWT sub bands such as approximation, horizontal, vertical and diagonal bands as shown in Figure 4. The significant information of signature is present in the approximation band whereas insignificant information such as edge information and detailed information are present in the horizontal, vertical and diagonals bands. The Standard Deviation (SD) of each sub bands is calculated using Equation 5 to obtain SD values and these values are considered as feature coefficients.

$$S = \left(\frac{1}{n} \sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2 \right)^{\frac{1}{2}}, \qquad (5)$$

Where $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$

n = number of elements in the vector x
x = number of pixel value in the column
$\bar{x}$ = Mean value

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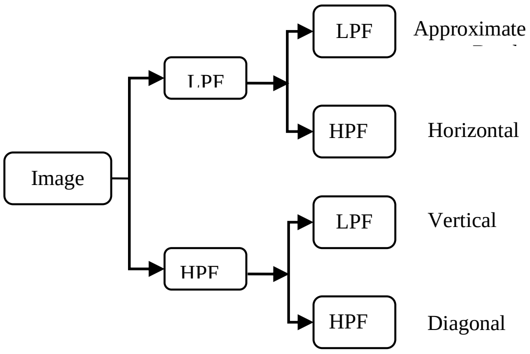

Fig.4. (a) Two level DWT decomposition

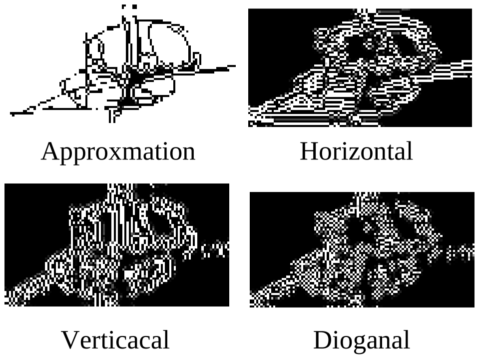

Fig.4. (b) 2D Discrete Wavelet Transform

(b) Spatial Domain Features:

The preprocessed signature is considered and spatial domain features are extracted leads to global features.

- Height of Signature: Scan the signature from top to bottom and measure the distance between two points in vertical projection.
- Width of Signature: Scan the signature from left to right and measure the distance between two points in horizontal projection.
- Diagonal Distance: The distance is measured from left to right diagonal distance of signature.
- Aspect Ratio: The ratio of width to height of signature.
- Center of gravity: It is calculated for signature image by adding all X and Y locations of gray pixels and dividing it by number of pixel counted.

$$\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x(t), \quad \bar{y} = \frac{1}{N}\sum_{t=1}^{N} y(t) \qquad (6)$$

Where
$\bar{x}$ = horizontal splitting across the signature image
$\bar{y}$ = vertical splitting across the signature image
N = Number of pixel count

- Area of black pixels: It is obtained by counting numbers of black pixels in the image.
- Middle Zone: It is between upper and lower edge limits of the image.
- Energy Features: Energy features of signature image are obtained using 1-D wavelet decomposition, which is the vector containing the percentages of energy corresponding to the approximation and detail band. The percentage value of energy for the approximate band is calculated and these values are considered as energy features.

Fusion: The obtained global features and DWT features are fused by concatenation to derive final set of feature vector.

IV. PROPOSED ALGORITHM

The proposed algorithm is used to identify signature effectively based on Global and DWT features.

The objectives are as follows:

1. To increase Total Success Rate.
2. To reduce False Acceptance Rate.

The Table 1 gives an algorithm of proposed model in which two biometric features are fused to get better performance results.

Table 1 Proposed Algorithm

Input: Genuine signature database, Test signature.
Output: Identification of signature.
Step 1: Signature image is read from data base.
Step 2: Signature image is Preprocessed.
Step 3: DWT Features are Extracted by applying DWT
Step 4: .Global Features are Extracted.
Step 5: Features of Global and DWT are Fused by concatenation.
Step 6: Repeat step 1 to 5 for test signature.
Step 7: Test features are compared with database features using Correlation Technique.
Step8: Image with correlation value more than threshold value is considered as matched image otherwise not matching.

Matching

The correlation technique is used to match the genuine signatures. The similarities between the train features vector set with the test features vector set are computed to determine FRR, TSR and FAR.

The correlation coefficients are calculated using Equation 7

$$R(x,y) = \frac{\Sigma XY - \Sigma X \Sigma Y}{\left(\left[N\Sigma X^2 - (\Sigma X)^2\right]\left[N\Sigma Y^2 - (\Sigma Y)^2\right]\right)^{1/2}} \qquad (7)$$

Where X= Genuine image feature vector set
Y= Skilled forgery image feature vector set
N= Length of feature vector

When correlation coefficient value is greater than threshold value signature is matched with its genuine signature otherwise not matching.

V. RESULT ANALYSIS

The GPDS signature data base images are considered for performance analysis. The value of FRR, FAR and TSR variations with different threshold values of global features is tabulated in Table 2. It is observed that values of FRR increase from 0% to 36.67% and TSR decrease from 100% to 63.34% as a threshold value increases but the value of FAR is decreases to 6.67% with threshold value increases.

Table 2 FRR, FAR and TSR variation with Threshold for Global Features

Threshold	%FRR	%FAR	%TSR
0.4	0	100	100

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0.5	0	100	100
0.55	0	96.67	100
0.6	0	93.34	100
0.65	0	90	100
0.70	0	83.32	100
0.75	0	63.34	100
0.80	6.67	53.34	93.34
0.81	6.67	53.33	93.34
0.82	6.67	40	93.34
0.83	6.67	40	93.34
0.84	6.67	33.34	93.34
0.85	6.67	33.34	93.34
0.90	36.67	6.67	63.34

The variation of FRR and FAR with threshold is shown in the Figure 5. It is noticed that as threshold value increase the FRR and FAR values increases and decrease respectively. The value of EER is 20%

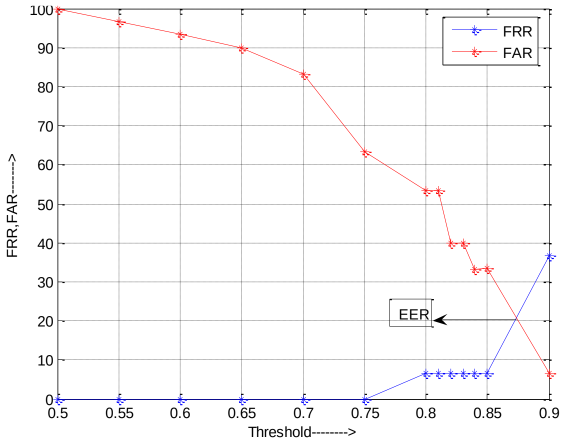

Fig.5. Graph of FAR and FRR with threshold value for Global Features.

The value of FRR, FAR and TSR variations with threshold for DWT features is tabulated in Table 3. It is observed that values of FRR increases from 0% to 100% as a threshold values increases. The values of FAR is decrease to 0% as a threshold values increases and TSR values is decreased to 0% with threshold.

Table 3 FRR, FAR and TSR variation with Threshold for DWT Features

Threshold	%FRR	%FAR	%TSR
0.4	0	100	100
0.5	0	100	100
0.55	0	100	100
0.6	0	100	100
0.65	0	93.34	100
0.70	0	90	100
0.75	0	63.34	100
0.80	6.67	13.34	93.34
0.81	6.67	10	93.34
0.82	6.67	6.67	93.34
0.83	6.67	6.67	93.34
0.84	6.67	6.67	93.34
0.85	6.67	3.34	93.34
0.90	100	0	0

The variation of FRR and FAR with threshold is shown in the Figure 6. It is observed that as threshold value increase the FRR and FAR values increases and decrease respectively. For threshold value of 0.9 the FRR become 100%. The FAR is 0% at threshold value is 0.9. The value of EER is 8%.

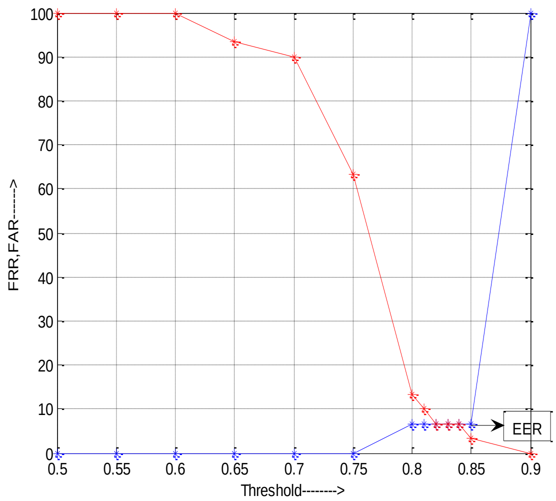

Fig.6. Graph of FAR and FRR with threshold value for DWT Features.

Table 4 shows the variation of FFR, FAR and TSR for different threshold and fusion values of global and DWT features. It is observed that values of FRR increase from 0% to 100% and TSR decrease from 100% to 0% as a threshold values increases but the value of FAR is decreases to 3.3% for threshold value of 0.81 and it further reduces to 0% as threshold value increases to 0.9.

Table 4 FRR, FAR and TSR variation with Threshold for Fusion Features

Threshold	%FRR	%FAR	%TSR
0.4	0	100	100
0.5	0	96.67	100
0.55	0	86.67	100
0.6	0	76.67	100
0.65	0	70	100

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0.70	6.67	43.34	93.3
0.75	6.67	6.67	93.3
0.80	6.67	3.33	93.3
0.81	40	3.33	60
0.82	40	0	60
0.83	46.67	0	53.34
0.84	100	0	0
0.85	100	0	0
0.90	100	0	0

The variation of FRR and FAR with threshold is shown in the Figure 7. It is noticed that as threshold value increase the FRR values increases and FAR decreases. For threshold value of 0.9 the FRR become 100% and FAR is 0%. The EER is 6.67%.

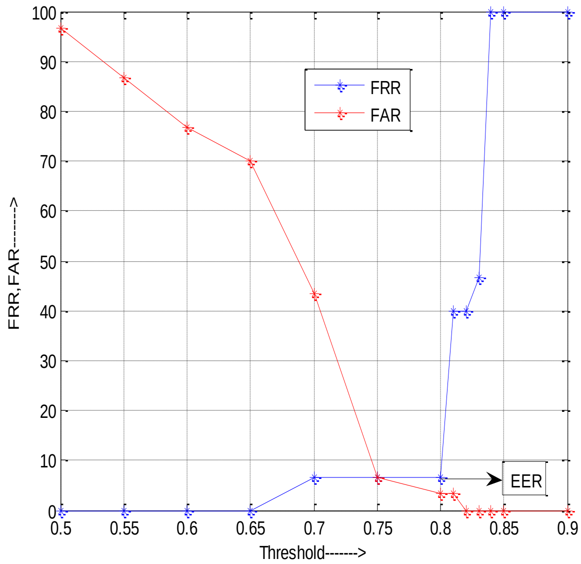

Fig.7. Graph of FAR and FRR with threshold value for Fusion of Features.

The percentage values of FAR of the proposed algorithm for different features set such as global, DWT and fusion of global and DWT features with different threshold values is tabulated in Table 5. It is observed that the value of FAR is reduced from 100% to 53.34% and 13.34% where the threshold varies from 0.5 to 0.8 for global features and DWT features respectively whereas FAR is reduced to 3.33% in fusion of global and DWT features with different threshold values. It is observed that the value of FAR is reduced in the case of proposed algorithm compared to the individual features of global and DWT.

Table: 5 FAR Comparision with Global, DWT and Fusion

Threshold	Global Features	DWT Features	Fusion of Global and DWT Features
	%FAR	%FAR	%FAR
0.5	100	100	96.67
0.55	96.67	100	86.67
0.6	93.34	100	76.67
0.65	90	93.34	70
0.70	83.32	90	43.34
0.75	63.34	63.34	6.67
0.80	53.34	13.34	3.33

The values of FAR for global, DWT and fusion with threshold are compared in the Figure 8. The FAR is very low i.e. 3.33% in fusion method comparing with other two methods such as global and DWT features.

The percentage values of FAR, FRR and EER are given in the Table 6 for the existing technique A Non-Rigid Feature Extraction Method for Shape Recognition [NRFEM] [16] and the proposed technique CSTSI. It is observed that the values of FAR, FRR and EER are improved in the case of proposed algorithm compared to the existing algorithm.

Table: 6 Comparison of FAR, FRR and EER with existing method NRFEM and proposed CSTSI method.

Methods	%FAR	%FRR	%EER
Existing Method [16]	28.78	19.37	24.16
Proposed Method	6.67	6.67	6.67

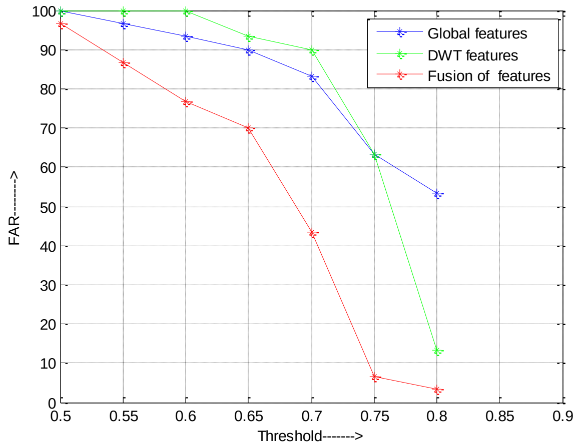

Fig.8. FAR vs. threshold for Global, DWT and Fusion Features

VI. CONCLUSION

In this paper CSTSI algorithm is propose to accept genuine signature and reject forged signature effectively. The global features and DWT features are extracted and concatenated to derive final set of features vectors. The test signature features are compared with database signature features using correlation technique. It is observed that the proposed fused technique gives better results compared to existing technique. In future the algorithm is tested using different kinds of transformation and fusion techniques with different databases to improve the performance parameters

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