Off-Line Signature Recognition Using Morphological Pixel Variance Analysis

H B Kekre, V A Bharadi
Computer Science Department
MPSTME, NMIMS University
Mumbai, India
+91-9323557897, +91-9819125676
hbk@yahoo.com,
vinu_bharadi@rediffmail.com

S Gupta
Computer Engineering Department
TCET, Mumbai University
Mumbai, India
+91-9820242661
shiwanigupta_om@live.com

A A Ambardekar, V B Kulkarni
Electronics Department
FAMT, Mumbai University
Ratnagiri, India
+91-9422431885
vinay291970@rediffmail.com

ABSTRACT
Handwritten signatures are one of the oldest biometric traits for human authorization and authentication of documents. Majority of commercial application area deal with static form of signature. In this paper we present a method for off-line signature recognition. We have used morphological dilation on signature template for measurement of the pixel variance and hence the inter class and intra class variations in the signature. The proposed feature extraction mechanism is fast enough so that it can be applied for on-line signature verification also.

Categories and Subject Descriptors
I.4.7 Image Processing and Computer vision

General Terms
Algorithms, Design, Experimentation, Security, Human Factors, Verification.

Keywords
Biometrics, Static Signature Recognition, Morphology.

1. INTRODUCTION
A problem of personal verification and identification is an actively growing area of research. The methods are numerous, and are based on different personal characteristics. Voice, lip movements, hand geometry, face, odor, gait, iris, retina, fingerprint are the most commonly used authentication methods. All of these and behavioral characteristics are called biometrics.

1.1 Biometrics
The biometrics is most commonly defined as measurable psychological or behavioural characteristic of the individual that can be used in personal identification and verification. The driving force of the progress in this field is, above all, the growing role of the Internet and the requirements of society. Therefore, considerable applications are concentrated in the area of electronic commerce and electronic banking systems and security applications of vital installations.

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The biometrics has a significant advantage over traditional authentication techniques (namely passwords, PIN numbers, smartcards etc.) due to the fact that biometric characteristics of the individual are not easily transferable, are unique of every person, and cannot be lost, stolen or broken. The choice of one of the biometric solutions depends on several factors [2]:

- User acceptance
- Level of security required
- Accuracy
- Cost and implementation time

Biometric and biomedical informatics are the fast developing scientific direction, studying the processes of creation, transmission, reception, storage, processing, displaying and interpretation of information in all the channels of functional and signal systems of living objects which are known to biological and medical science and practice. Modern natural sciences at present sharply need in the updating of scientific picture of the world, and the essential contribution in this process can be made by the biometric and biomedical methods. Only some more simple (statistical) forms of biometric and biomedical information have found their application when person identification, and raised interest for these methods of identification can be caused by new possibilities of information technologies.

1.2 Handwritten Signature Recognition
Handwritten signature verification has been extensively studied & implemented. Its many applications include banking, credit card validation, security systems etc. In general, handwritten signature verification can be categorized into two kinds – on–line verification and off–line verification [3][10][21]. On–line verification requires a stylus and an electronic tablet connected to a computer to grab dynamic signature information [21]. Off–line verification, on the other hand, deals with signature information which is in a static format.

In On–line approach we can acquire more information about the signature which includes the dynamic properties of signature. We can extract information about the writing speed, pressure points, strokes, acceleration as well as the static characteristics of signatures [22]. This leads to better accuracy because the dynamic characteristics are very difficult to imitate, but the system requires user co-operation and complex hardware. Digitizer tablets or pressure sensitive pads are used to scan signature dynamically, one such tablet is shown in Figure 1.

Figure 1. Digitizer Tablet for On-line Signature Scan

In off–line signature recognition we are having the signature template coming from an imaging device, hence we have only static characteristic of the signatures. The person need not be present at the time of verification. Hence off-line signature verification is convenient in various situations like document verification, banking transactions etc. [1][12][13][14]. As we have a limited set of features for verification purpose, off-line signature recognition systems need to be designed very carefully to achieve the desired accuracy.

1.3 Steps in Signature Recognition [12][22]

Signature Recognition Systems need to preprocess the data. It includes a series of operations to get the results. The major steps are as follows

1.3.1 Data Acquisition

The signatures to be processed by the system should be in the digital image format. We need to scan the signatures from the document for the verification purpose

1.3.2 *Signature Pre-processing*

We have to normalize the signature, resize it to proper dimensions, remove the background noise, and thin the signature. This yields a signature template which can be used for extracting the features. A typical scanned and Pre-Processed Signature is shown in Figure 2.

Figure 2. Pre-processing of a signature

1.3.3 Feature Extraction

In this paper we are using morphological contours of the signature and their overlapping map as a feature vector. These contours are generated by multiple morphological dilation of the signature.

1.3.4 Enrollment & Training

The extracted features are stored in to database. The human signature is dependent on varying factors, the signature characteristics change with the psychological or mental condition of a person, physical and practical condition like tip of the pen used for signature, signatures taken at different times, aging etc.

We have to consider a high degree of intra-class variation because two signatures from a same person are never same. Our system should consider this variation and at the same time the system should possess high degree of accuracy to detect forged signatures.

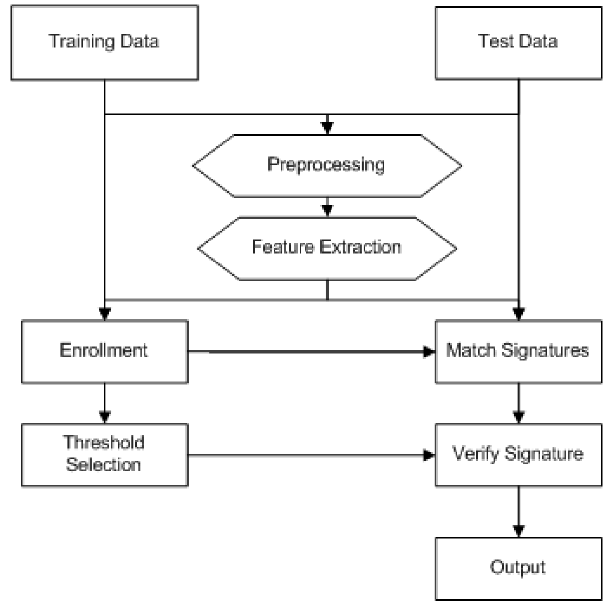


Figure 3. Simplified workflow for a typical Signature Recognition System

We train the system using a training set of signature obtained from a person. Designing of a classifier is a separate area of research. The decision thresholds required for the classification are calculated by considering the variation of features among the training set. Separate set of thresholds (user Specific) is calculated for each person enrolled, some system also use common threshold for all users.

1.3.5 Performance Evaluation

The performance of system depends on how accurately the system can classify between the genuine and fraud signatures. The forgeries involved in handwritten signatures have been categorized based on their characteristic features [5].

2. OFF-LINE SIGNATURE RECOGNITION

A lot of research has been done in the field of Off-line signature recognition. This is a convenient approach and various optimization techniques are applied to address the problem. Sabourin [23] used granulometric size distributions for the definition of local shape descriptors in an attempt to characterize the amount of signal activity exciting each rectangle on the focus of a superimposed grid. He then used a nearest neighbor and threshold-based classifier to detect random forgeries. A total error rate of 0.02% and 1.0% was reported for the respective classifiers. A database of 800 genuine signatures from 20 writers is used.

Abbas [20] used a back propagation neural network prototype for the offline signature recognition. He used feed forward neural networks and three different training algorithms Vanilla, Enhanced and batch were used. In [20] he reported FAR between the range of 10-40 % for casual forgeries. A neuro-fuzzy system was proposed by Hanmandlu [30], they compared the angle made by the signature pixels that are computed with respect to reference points and the angle distribution was then clustered with fuzzy c-means algorithm. Back propagation algorithm was used for training neural network. The system reported FRR in the range of 5-16% with varying threshold.

Zhang [6] have proposed a Kernel Principal Component Self-regression (KPCSR) model for off-line signature verification and recognition problems. Developed from the Kernel Principal Component Regression (KPCR), the self-regression model selected a subset of the principal components from the kernel space for the input variables to accurately characterize each person's signature, thus offering good verification and recognition performance. The model directly worked on bitmap images in the preliminary experiments, showing satisfactory performance. A modular scheme with subject-specific KPCSR structure proved to be very efficient, from which each person was assigned an independent KPCSR model for coding the corresponding visual information. He reported FRR 92% and FAR .5%

Baltzakis [14] developed a neural network-based system for the detection of random forgeries. The system uses global features, grid features (pixel densities), and texture features (co occurrence matrices) to represent each signature. For each one of these feature sets, a special two-stage perceptron one-class-one-network (OCON) classification structure is implemented. In the first stage, the classifier combines the decision results of the neural networks and the Euclidean distance obtained using the three feature sets. The results of the first stage classifier feed a second-stage radial basis function (RBF) neural network structure, which makes the final decision. A database is used which contains the signatures of 115 writers, with between 15 and 20 genuine signatures per writer. An average FRR and FAR of 3%and 9.8%, respectively is obtained. In [25] Armand, Blumenstein and Muthukkumarasamy used combination of the Modified Direction Feature (MDF) in conjunction with additional distinguishing features to train and test two Neural Network-based classifiers. A Resilient Back Propagation neural network and a Radial Basis Function neural network were compared. Using a publicly available database of 2106 signatures containing 936 genuine and 1170 forgeries, they obtained a verification rate of 91.12%.

Justino [15] used a discrete observation HMM to detect random, casual, and skilled forgeries. A grid segmentation scheme was used to extract three features: a pixel density feature, a pixel distribution feature (extended-shadow-code), and an axial slant feature. A cross-validation procedure was used to dynamically define the optimal number of states for each model (writer). Two data sets are used. The first data set contains the signatures of 40 writers with 40 genuine signatures per writer. This data set was used to determine the optimal codebook size for detecting random forgeries. This optimized system was then used to detect random, casual, and skilled forgeries in a second data set. The second data set contains the signatures of 60 writers with 40 training signatures, 10 genuine test signatures, 10 casual forgeries, and 10 skilled forgeries per writer. An FRR of 2.83%and an FAR of 1.44%, 2.50%, and 22.67% are reported for random, casual, and skilled forgeries, respectively.

Kaewkongka, Chamnongthai and Thipakom [30] proposed a method of off-line signature recognition by using Hough transform to detect stroke lines from signature image. The Hough transform was used to extract the parameterized Hough space from signature skeleton as unique characteristic feature of signatures. In the experiment, the Back Propagation trained Neural Network was used as a tool to evaluate the performance of the proposed method. The system was tested with 70 test signatures from different persons. The experimental results reveal the recognition rate 95.24%

Fang [7] developed a system that is based on the assumption that the cursive segments of forged signatures are generally less smooth than that of genuine ones. Two approaches are proposed to extract the smoothness feature: a crossing method and a fractal dimension method. The smoothness feature is then combined with global shape features. Verification is based on a minimum distance classifier. An iterative leave-one-out method is used for training and for testing genuine test signatures. A database with 55 writers is used with 24 training signatures and 24 skilled forgeries per writer. An AER of 17.3% is obtained.

Ferrer, Alonso, and Travieso [16], used Offline Geometric Parameters for Automatic Signature Verification Using Fixed-Point Arithmetic. They used set of geometric signature features for offline automatic signature verification based on the description of the signature envelope and the interior stroke distribution in polar and Cartesian coordinates. The feature set was calculated using 16 bits fixed-point arithmetic and tested with different classifiers, such as hidden Markov models, support vector machines, and Euclidean distance classifier. FRR reported was 2.12% and FAR was 3.13%. S. Audet, P. Bansal, and S. Baskaran [40], designed Off-Line Signature Verification and Recognition using Support Vector Machine. They used global, directional and grid features of signatures. Support Vector Machine (SVM) was used to verify and classify the signatures and a classification ratio of 0.95 was obtained.

Deng [19] developed a system that used a closed contour tracing algorithm to represent the edges of each signature with several closed contours. The curvature data of the traced closed contours were decomposed into multi-resolution signals using wavelet transforms. The zero crossings corresponding to the curvature data were extracted as features for matching. A statistical measurement was devised to decide systematically which closed contours and their associated frequency data were most stable and discriminating. Based on these data, the optimal threshold value which controls the accuracy of the feature extraction process was calculated. Matching was done through dynamic time warping. Experiments were conducted independently on two data sets, one consisting of English signatures and the other consisting of Chinese signatures. For each experiment, twenty-five writers are used with ten training signatures, ten genuine test signatures, ten skilled forgeries, and ten casual forgeries per writer. When only the skilled forgeries are considered, AERs of 13.4% and 9.8% are reported for the respective data sets. When only the casual forgeries are considered, AERs of 2.8% and 3.0% are reported.

Majhi, Reddy and Prasanna [5] proposed a morphological parameter for signature recognition, they proposed center of mass of signature segments, and the signature was split again and again at its center of mass to obtain a series of points in horizontal as well as vertical mode. The point sequence is then used as discriminating feature; the thresholds were selected separately for each person. They achieved FRR 14.58% and FAR 2.08%. This concept of geometric centers is used in this project, here we extend the concept to find successive geometric centers of depth 2 and use them as a set of global features.

Table.1 Performance Comparison with Off Line Signature Recognition Systems

Sr.	Approach	FAR	FRR	Accuracy
1	**Signature Recognition using Morphological Pixel Variance Analysis (Proposed System)**	**6.56**	**3.7**	**94.94**
2	Contour Method [28]	11.60	13.20	86.90
3	Exterior Contours and Shape Features[27]	06.90	06.50	93.80
4	Local Granulometric Size Distributions [23]	07.00	05.00	-
5	Back-Propagation Neural Network Prototype [21]	10.00	06.00	-
6	Geometric Centers [5]	09.00	14.58	-
7	Two-stage neural network classifier [11]	03.00	09.81	80.81
8	Distance Statistics [18]	34.91	28.30	93.33
9	Modified Direction Feature [25]	-	-	91.12
10	Hidden Markov Model and Cross-Validation [15]	11.70	00.64	-
11	Discrete Random Transform and a HMM [12]	10.00	20.00	-
12	Kernel Principal Component Self-regression [6]	03.40	08.90	-
13	Parameterized Hough Transform [30]	-	-	95.24
14	Smoothness Index Based Approach [8]	-	-	79.00
15	Geometric based on Fixed-Point Arithmetic [16]	4.9-15.5	5.61-16.39	-
16	HMM and Graphometric Features [13]	23.00	01.00	-
17	Virtual Support Vector Machine [26]	13.00	16.00	-
18	Wavelet–based Verification [19]	10.98	05.60	-
19	Genetic Algorithm [31]	01.80	08.51	86.00

Kekre and Pinge used template matching approach in [29]. The signature was segmented in predefined shape templates, in all 40 different templates were considered for feature extraction. They used neural network classifier. Two separate algorithms were used first algorithm used 40 shapes associated with each signature, neural network with 40 input nodes , 25 nodes in hidden layer and 10 nodes in output layer was used. The other algorithm used ratio vectors for all the signatures and all these vectors were used to train a neural network with 450 input nodes, 230 nodes in hidden layer and 10 nodes in output layer. Total 10 users database was used for testing, their algorithm 1 reported FAR 20% and algorithm 2 reported FAR 0%.

All of these efforts were towards automating the process of handwritten signature recognition. We have defined our project scope previously. Here we try to develop a signature verification system over the guidelines set by these people. Table I gives the summary of all systems performance metrics.

3. CONTOUR GENERATION

The scanned signature is first pre-processed to get a normalized binary template. We follow a series of operations like noise removal using filtering, Scaling, Smoothening, Intensity normalization, Thinning [1][6]. This gives us a binary signature template. We use the normalized template for further processing. The signature has intra-class variations i.e. Signatures of a same user have variations, but these variations are limited. Forged signatures (Simple forgeries) and different user's signatures have vast variations (Inter – Class variations). We try to detect these variations in signature segments. The signature pixels are having specific limit of variation for the genuine set of signature and the forgeries have variations greater than the limit of a specific person's signature. We try to classify the signature based on this variation. To quantify this variance we have used the proposed morphological [9] technique.

We generate a contour of signature; this contour is actually the external boundary of the signature. Dilation algorithm is used for this and various levels of dilations are used. We use morphological dilation process with three different structuring elements; the structuring elements [9] are circles with radius r1, r2, r3, r4 these radii correspond to the allowed pixel variance. This process gives four dilated sets D1, D2, D3, and D4 as shown below,

$$D_i = S \oplus B_i \tag{1}$$

Where S=Signature template Bi = structuring element- Circle of Radius r_i, i=1, 2, 3.

This is achieved in programming environment by drawing circles of various radii on the templates and filling them with appropriate colour; the circles are drawn with radii r1, r2, r3, r4. Where r4 > r3 > r2 > r1. This operation gives a structure with bands of varying thickness. These bands of colours will represent the variation extent of each pixel and hence the signature segments. This structure is shown in Fig. 4.The four bands in the testing program were generated with r1=3 Pixel, r2=6 Pixel, r3=10 Pixel and r4=16 Pixel radius and filled with Black, Red, Green, Blue Colours Respectively.

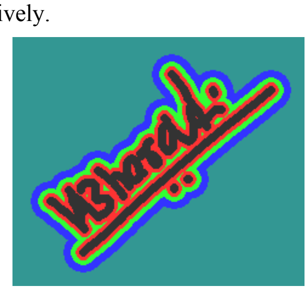


Figure 4. Check Pattern for standard Signature shown in Figure 2.

The colours are represented in (R, G, B) format where Red =(255,0,0) , Green=(0,255,0), Blue=(0, 0, 255) and white=(255,255,255), Black=(0, 0, 0). We call this bands pattern as a "Check pattern". In the next section we discuss detection process.

3.1 Pixel Variance Analysis

For training purpose we take three standard signatures from a user and generate dilation sets Di and same band structure for them. For detection purpose we use two templates at a time, one is the test signature and one from the standard templates. Similar check pattern is generated for the test signature. The test template 'T' will be used to generate the dilation sets we get four test dilation sets as discussed above with the help of structuring elements

$$TD_i = T \oplus B_i \qquad (2)$$

TDi= test dilation pattern, Bi = structuring element- Circle of Radius r_i. i=1, 2, 3, 4.

Now consider each of this dilation set as an allowable pixel variation area, we have the lowest dilation band D1 as the 3 pixel dilated signature template as the allowed variation and if any pixel is going outside this region will be a misplaced pixel of high variation pixel. If the pixel from test signature are going in the higher dilation bands of original signature Di then they have variation more than the specified radius of the band, we can count the number of pixels from test signature which are having such variation by set intersection process. We take the intersection of dilation sets and try to find the cross occurrence. This is given by

$$C_{ij} = D_i \cap TD_j \quad \text{……. i,j=1, 2 ,3, 4.} \qquad (3)$$

The lowest variation band is C_{00} , We find the element count for each set for Cij if i≠j then it is cross intersection and corresponding to the variation pixel. The values of i, j correspond to different degree of variation. We count the number of pixel in each band.

For genuine signatures with least variation the element count of Cij where i=j is very high and C_{00} contain the perfect of least variation pixels. Higher is the element count higher is the matching. If the element content of cross intersection is high i.e. Cij , where i≠j then the pixels are having more variation and correspond to mismatch.

Each set is given a weight Wij corresponding to degree of match, we evaluate the matching score S as follows, Wij (i=j) > Wij (i≠j).

$$S = \sum_{i=1}^{i=4} \sum_{j=1}^{j=4} NCij * Wij \qquad (4)$$

Values of Wij are based on intra class variation and evaluated by correlation of same person's signature and evaluating the variation or we can set static values by trial & error process. The higher the value of 'S' higher is the matching between the template. We can set a threshold for 'S' to classify the signatures.

In Table 5, we have shown one persons signature taken for calculation of the above discussed parameters, the limits for the acceptance levels are Limit 1 to Limit 5, depend on the intra class variations. The feature extraction process is discussed in next section.

3.2 Practical Implementation

We have implemented the algorithm mentioned above in Visual Basic 6.0. To find the intersection of sets we evaluate the bitwise Exclusive OR (EX-OR) of the colour bands generated by the dilation process. This is illustrated as follows, First template

sign1(x, y) …..x=0,1…..N , y=0,1…..M (5)

For a M Rows X N Columns template.

Second template

sign2(x, y) …..x=0,1…..N , y=0,1…..M (6)

for a M rows X N Columns template.

EX-OR operation will generate third template test(x, y) where

$$\text{test}(x_i, y_i) = \text{sign1}(xi, yi).(R,G,B) \oplus \text{sign2}(xi, yi).(R,G,B) \qquad (7)$$

This EX-OR operation will be performed on the (R, G, B) colour triplet of each pixel because of this in the test(x, y) template various colours are generated by the EX-ORing of R G B bands R(255,0,0) Ex-Or G(0,255,0) will yield (255,255,0) If same colour is there it will generate White(0, 0, 0).

Black (0, 0, 0) Ex-Ored with Any of the R, G, B bands will give the same colour only i.e. R, G, B only. The R G B bands in sign template are actually the allowed variations for the pixel and if the pixel is in the allowed variations it will generate Either of the pure R, G, B or otherwise any combination of R, G, B.

Pure Black pixels are un-deviated pixels (Black (0, 0, 0) Ex-Or Black (0, 0, 0) Will give (0, 0, 0) i.e. Black only). By scanning the check pattern generated we can find out the pixel variance and hence the matching of signature template, The colour codes used are as follows in Table 2.

Table 2. Colour codes used in program

Colour	R	G	B
0. Black	0	0	0
1. Red	255	0	0
2. Green	0	255	0
3. Blue	0	0	255
4. Background colour	0	100	96
5. White	255	255	255
6. Colour1	0	252	255
7. Colour2	255	8	255
8. Colour 3	255	252	0
9. Test result background	255	156	168

4. Results

We consider a set of six signatures for a person as shown in Table 3, Signature 1 to 3 are genuine and Signature 4 to 6 are forgery.

We perform the dilation based contour analysis and the check pattern generated is shown in the same figure. Next step of the operation is to scan this check pattern and count the number of pixels of each colour, Red (NR), Green (NG), Blue (NB), Black (NBK) and White (NW) respectively.

Table 3. Test Signatures & Corresponding Matching pattern Generated

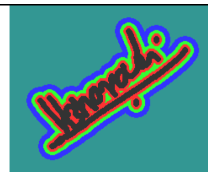
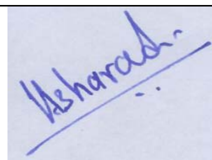
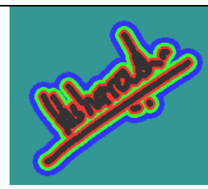
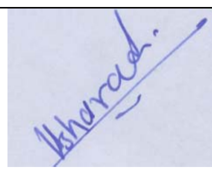
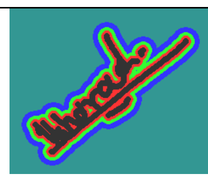
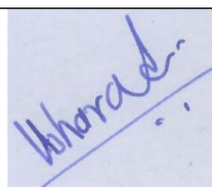
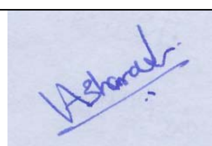
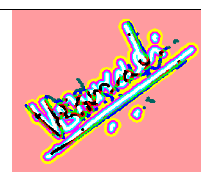
Sr. No.	Signature	Check Pattern	Matching Pattern	Result
1				Acceptable 60.3%
2				Okay 64.6%
3				Okay 65.32%
4			No Check pattern Generated	Rejected Drastic Scale Change
5				Rejected 28.9%
6				Rejected 23.29%

Table 4. Results

Parameter	Sign1	Sign2	Sign3	Sign4	Sign5	Sign6
Black Pixel	43.91	44.37	57.2	0	30.35	29.09
Red Pixel	21.78	28.66	30.1	0	24.68	21.01
Green Pixel	17.73	25.07	17.68	0	28.84	31.56
Blue pixel	9.32	11.51	7.5	0	21.11	27.6
Missing or Extra	-1.65	-6.04	3.05	0	-13.28	-16.85
Original Pixels	10.496	10.49	12.26	0	10.137	10.137
Test Sign Pixels	10.661	11.11	11.901	0	11.465	11.795
Matching	60.3	64.6	65.32	0	28.96	23.29
Remarks	Acceptable	Okay	Okay	Rejected	Rejected	Rejected

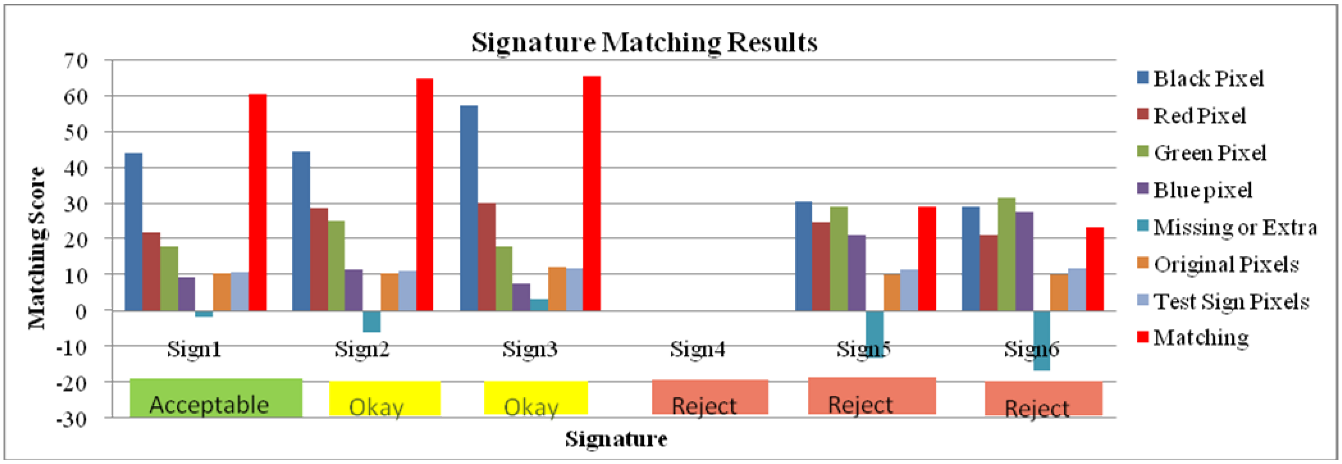


Figure 5. Matching Results for Signature 1 to 6

We give these parameters as inputs to a fuzzy classifier. The fuzzy logic detector has four participation sets Perfect, Good, Acceptable and Rejected, for which the output of fuzzy network is given .The matching pattern and the percentage matching obtained are shown in Table 4 & Figure 5. Normalized parameters are shown in these illustrations. Figure 5 Shows that Signature 1 to 3 have high degree of matching and they are accepted as a match, whereas signatures 4 to 6 are rejected due to low matching score.

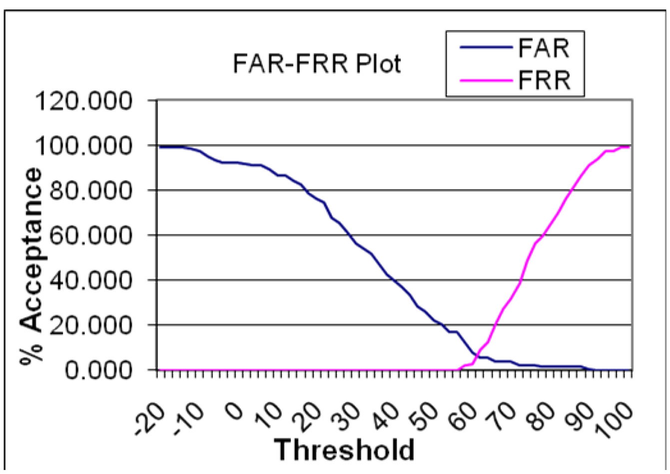


Figure 6. FAR-FRR Plot for Signature Recognition System (EER = 6.1%)

This method was tested on signatures from the database collected from approx100 individuals, from each person minimum 4 to max 12 signatures were collected, three signatures each were used for feature extraction & training and remaining signature used for testing. Forged signatures from volunteers were collected for testing purpose; the database consists of around 1000 genuine signatures, 350 different levels of forgeries. Total 257 tests were performed, Table 5 gives the summary.Figure 6 shows the FAR-FRR plot for the system. The system has achieved EER of 6.1% at 63% Threshold level.

Next we present the classified results in Table 6, we present system performance calculated separately for the Genuine and forged signatures. In the forged signature group we further have group of Casual and Skilled forgery signatures.

Table 5. Signature recognition results

Recognition Mode Inputs Test Signatures		**Accepted/ Rejected Signatures**		**Performance Metrics %**	
Cases That Should be Accepted	135	Cases Actually Accepted	130	TAR	**96.30**
		Cases Falsely Rejected	05	FRR	**3.70**
Cases That Should be Rejected	122	Cases Actually Rejected	114	TRR	**93.44**
		Cases Falsely Accepted	08	FAR	**6.56**

The system is having 100% Accuracy for the rejection of casual forgery and for skilled forgery the False Acceptance ratio is 5.79%. For the genuine signatures True Acceptance Ratio is 92.77%.

Table 6. Performance Metrics for Final System

Test Samples			**Ratio**	**Results obtained on the given test bed (%)**
All sample of a subject	Genuine		TAR	92.77
			FRR	7.23
	Forged	Casual	FAR	00.00
			TRR	100.00
		Skilled	FAR	05.79
			TRR	94.21

5. Conclusion

Here we have presented an off-line signature recognition system based on the pixel variance analysis by multiple morphological dilations. The system is based on an EX-OR template matching based fuzzy classifier. This is a contour based signature recognition technique. Along with various parameters like number of pixels, Angle of rotation, width, height we are using check pattern generated by multiple morphological dilation. We are using check pattern to find out variation in signature pixels. The system developed has reported 94.94% accuracy. The FAR is 6.56% and FRR is 3.7%. The system performance can be improved further by using more training signature and neuro-computing approach.

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