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Off-Line Signature Recognition Systems

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ABSTRACT
Handwritten signature is one of the most widely used biometric traits for authentication of person as well as document. In this paper we discuss issues regarding off-line signature recognitions. We review existing techniques, their performance and method for feature extraction. We discuss a system designed using cluster based global features which is a multi algorithmic offline signature recognition system.

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

General Terms
Algorithms, Performance, Design, Security, Verification.

Keywords
Signature Recognition & Verification, Biometrics.

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.

1.1Biometrics
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.

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

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.

1.2Handwritten 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][35]. On–line verification requires a stylus and an electronic tablet connected to a computer to grab dynamic signature information [35]. Off–line verification, on the other hand, deals with signature information which is in a static format.

Figure 1. Digitizer Tablet for On-line Signature Scan

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 [36]. 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.

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.

1.3Steps in Signature Recognition [12][36]

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

We are using various feature extraction algorithms. The feature set includes the conventional global features of signature as well as new features. The new features that are proposed include Walsh coefficient of pixel distribution, codeword Histogram based on clustering technique (Vector Quantization), spatial moments of codeword, Grid & Texture features, and Successive Geometric centers of depth 2.

1.3.4Enrollment & 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.

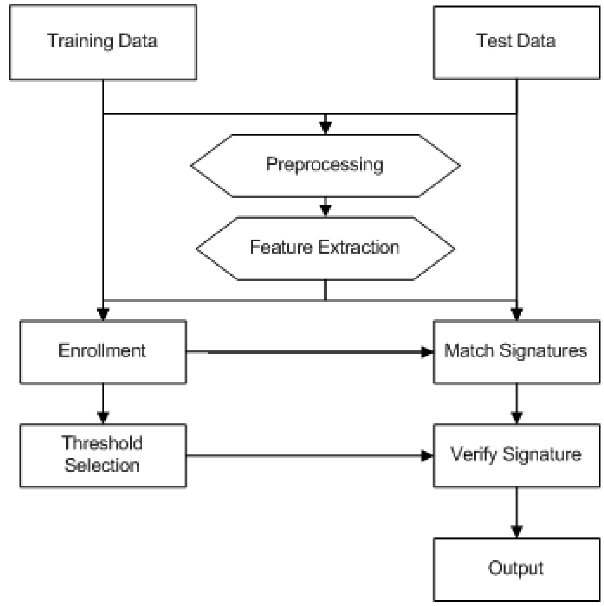

Figure 3. Simplified workflow for a typical Signature Recognition System

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 form all users.

1.3.5Performance 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].

1.4Level of Forgeries [5]

Various kinds of forgeries are classified into the following types:

1.4.1Random Forgery

The signer uses the name of the victim in his own style to create a forgery known as the simple forgery or random forgery. This forgery accounts for the majority of the forgery cases although they are very easy to detect even by the naked eye

1.4.2Unskilled Forgery

The signer imitates the signature in his own style without any knowledge of the spelling and does not have any prior experience. The imitation is preceded by observing the signature closely for a while.

1.4.3Skilled Forgery

Undoubtedly the most difficult of all forgeries is created by professional impostors or persons who have experience in copying the signature. For achieving this one could either trace or imitate the signature by hard way. Figure 4 shows the different types of forgeries and how much they are varies from original signature.

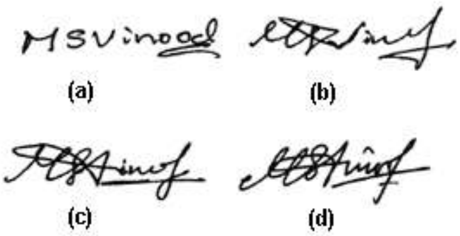

Figure 4. Type of forgeries a) Random Forgery b) Unskilled Forgery c) Skilled Forgery d) Original Signature

The two legal properties of a handwritten signature [14] are briefly stated below:

• Integrity-the signature establishes the integrity of the signed document, indicating that it has not been altered in any way.

• Non-repudiation-the accumulated effect of the above factor promises such a high degree of purpose that the signer cannot deny he or she has signed.

Signature recognition & Verification Systems are designed for detecting these levels of forgeries. While detecting forgeries the system should not reject signatures from legitimate users. The performance evaluation metrics such as False Acceptance Ratio (FAR), False Rejection Ratio (FRR) & Equal Error Rate (EER) [14][31][36] are evaluated for the system. To perform detection the system extract features from the signature template, our main interest is off-line signature recognition, and we discuss typical features and their extraction mechanism in the next section.

2.Signature Recognition Systems (SRS)

A popular means of authentication historically has been the handwritten signature. Though such signatures are never the same for the same person at different times, there appears to be no practical problem for human beings to discriminate visually the real signature from the forged one. It will be extremely useful when an electronic device can display at least the same virtuosity. The development of computer–aided handwritten signature verification systems has been ongoing for decades. Different approaches are developed to deal with the handwritten signature recognition problem.

2.1Hardware Approach

The hardware approach is faster and convenient, Texas instruments has come up with a DSP chip TMS320. This is a family of digital signal processors which is capable of handling neural clustering techniques to enhance the discriminating power and arrive at a very simple and low-cost solution that can be embedded in existing pen-based systems, such as handheld computers and transaction units. Dullink and Dallen [16] have reported FRR up to 1% and FAR up to 0.01% using TMS320 family.

2.2On-line Approach

On-line signature recognition considers the dynamic characteristics of signatures. In [3] Jain & Greiss have used critical points, speed curvature angle as features and they have reported FRR 2.8% and FAR 1.6 %. They used common as well as writer dependent thresholds but it was observed that the writer dependent thresholds give better accuracy.

Considering another approach Lei, Palla and Govindarajalu [15] have proposed a technique for finding correlation between two signature sequences for online recognition, they mapped the occurrence of different critical points on signature and the time scale and the correlation between these sequences was evaluated using a new parameter called Extended Regression Square (ER^2) coefficient the results were compared with an existing technique based on Dynamic Time Wrapping (DTW). They reported Equal Error rate (EER) 7.2% where the EER reported by DTW was 20.9 % with user dependent thresholds. Abdullah and Shoshan [1] used Image invariant and dynamic features for On-Line signature recognition , they used the Fourier descriptors for invariance and writing speed was used as dynamic feature. Multi layer perceptron neural network was used for classification.

In [47] Rhee and Cho used Model guided segmentation approach for segment–to–segment comparison to obtain consistent segmentation. They used discriminative feature selection for skilled as well as random forgeries. They reported EER 3.4 %. Nalwa [48] used a moment and torque base approach for on-line signature recognition. His work is based parameterizing each on-line curve over its normalized arc-length. These parameters are then represented along the length of the curve, in a moving coordinate frame. The measures of the curve within a sliding window that are analogous to the position of the center of mass, the torque exerted by a force, and the moments of inertia of a mass distribution about its center of mass. Further, He suggested the weighted and biased harmonic mean as a graceful mechanism of combining errors from multiple models of which at least one model is applicable but not necessarily more than one model is applicable. He recommended that each signature be represented by multiple models, these models, perhaps, local and global, shape based and dynamics based. The reported FRR was 7% and FAR was 1%.

Keit, Palanjppan used a pen pressure based method for online mode in [46] They designed a system which used a specialized pen capable of sensing writing pressure of the person and then used the pressure signal for identification purpose. They have obtained FRR 2.13% and FAR 3.14%. Shafiei & Rabiee [44] have proposed a method based on variable length segmentation & Hidden Markov Model (HMM). J. hasna [22] have proposed a neural network based prototype for dynamic signature recognition, the system used method of verification by the Conjugate Gradient Neural Network (NN), and the FRR achieved was 1.6%. This was a brief review of the on-line signature recognition. Next we consider the off-line approach for signature recognition.

2.3Off-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 [37] used granulometric size distributions for the definition of local shape descriptors in an attempt to characterize the amount of signal activity exciting each retina on the focus of an 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 [34] 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 [34] 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 are computed with respect to reference points and the angle distribution was then clustered with fuzzy c-means algorithm. Back propagation algorithm 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 [39] 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 [20] 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 [45] proposed a method of an 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 [28], 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 [33] 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.

Table I

Performance Comparison with Off Line Signature Recognition Systems

Sr.	Approach	FAR	FRR	Accuracy
1	**Signature Recognition using Clustering Technique (Proposed System)**	**2.5/8.2**	**6.5/2.96**	**95.08**
2	Contour Method [42]	11.60	13.20	86.90
3	Exterior Contours and Shape Features[41]	06.90	06.50	93.80
4	Local Granulometric Size Distributions [37]	07.00	05.00	-
5	Back-Propagation Neural Network Prototype [34]	10.00	06.00	-
6	Geometric Centers [5]	09.00	14.58	-
7	Two-stage neural network classifier [14]	03.00	09.81	80.81
8	Distance Statistics [31]	34.91	28.30	93.33
9	Modified Direction Feature [39]	-	-	91.12
10	Hidden Markov Model and Cross-Validation [20]	11.70	00.64	-
11	Discrete Random Transform and a HMM [17]	10.00	20.00	-
12	Kernel Principal Component Self-regression [6]	03.40	08.90	-
13	Parameterized Hough Transform [45]	-	-	95.24
14	Smoothness Index Based Approach [8]	-	-	79.00
15	Geometric based on Fixed-Point Arithmetic [28]	4.9-15.5	5.61-16.39	-
16	HMM and Graphometric Features [18]	23.00	01.00	-
17	Virtual Support Vector Machine [40]	13.00	16.00	-
18	Wavelet–based Verification [33]	10.98	05.60	-
19	Genetic Algorithm [51]	01.80	08.51	86.00

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.

Kekre and Pinge used template matching approach in [43]. 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 algorithm 1 reported FAR 20% and algorithm 2 reported FAR 0%.

Table II

Performance Comparison with On Line & Hardware Based Signature Recognition Systems

Sr.	Approach	FAR	FRR	EER	Accuracy
1	ER2 – Dynamic Time Wrapping [15]	-	-	7.20	-
2	On line SRS - Digitizer Tablet [3]	7.50-1.10	03.90	-	-
3	Image Invariants and Dynamic Features [1]	-	-	-	83.00
4	On Line SRS Model Guided Segmentation [47]	0.80	-	3.40	
5	Conjugate Gradient Neural Networks [27]	-	-	-	98.40
6	Consistency Functions [48]	01.00	07.00	-	-
7	Variable Length Segmentation and HMM [44]	04.00	12.00	11.50	-
8	Implementing a DSP Kernel [16]	< 0.01	-	-	>99.00

9	Dynamic Feature of Pressure [24]	6.80	10.80	-	-
10	Low cost Dynamic SRS [10]	7.00	6.00	-	-

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 peoples. Next we discuss the very important step of signature recognition that is the pre-processing of a signature. Table I & II give summary of all the systems performance metrics.

3.Experiment

Authors have designed a multi algorithmic signature recognition system which takes into account the conventional features as discussed above as well as it combines some of the prominent feature extraction mechanisms with newly proposed cluster based global features to develop an Off-line signature recognition system. For the signature shown in Figure 2. The conventional features are as follows in table III.

Table III

Feature Extracted from signature shown in Figure 2

Sr.	Feature	Extracted Value
1	Number of pixels	**547**
2	Picture Width (in pixels)	**166**
3	Picture Height (in pixels)	**137**
4	Horizontal max Projections [12]	**12**
5	Vertical max Projections [12]	**15**
6	Dominant Angle-normalized [12]	**0.694**
7	Baseline Shift (in pixels)	**47**
8	Trisurface Area1 [25]	**0.151325**
9	Trisurface Area2 [25]	**0.253030**
10	Trisurface Area3 [25]	**0.062878**

We have proposed following global as well as cluster based features, for extracting information in pixel distribution of the signature

3.1Walsh transform of the vertical & horizontal pixel projections

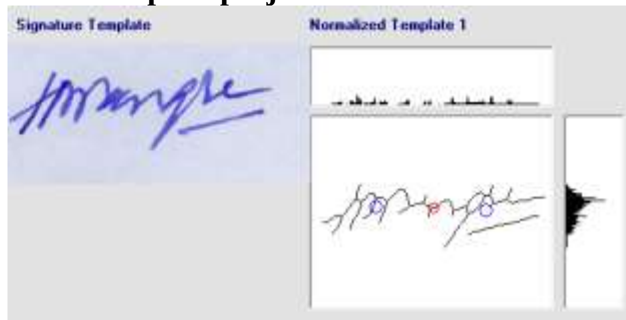

Figure 5. Signature and its horizontal and vertical pixel distributions

We use Hadamard transform to the horizontal pixel distribution points (Hi) and vertical pixel distribution points (Vi); Hadamard transform is fast to calculate and gives moderate energy compaction. This operation gives the horizontal Hadamard coefficients (HH_i) and vertical Hadamard coefficients (VH_i). We use Kekre's [21] algorithm to get the Walsh coefficients from the Hadamard coefficients. This operation yields Walsh coefficients of the histograms (SHH_i, SVH_i). The coefficients are plotted and shown in Figure 6. This is used as feature vector.

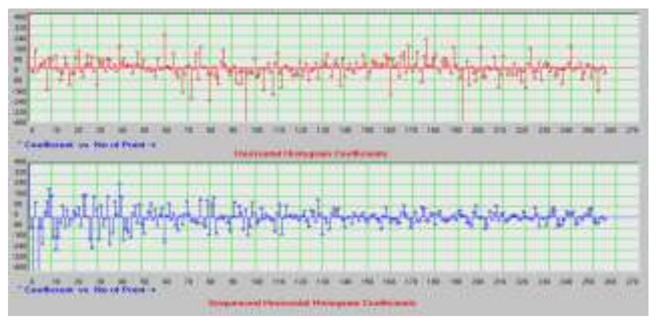

Figure 6 Hadamard Coefficients of Horizontal pixel distribution (Upper Plot) and their sequenced arrangement (Lower Plot) of the signature mentioned in Figure 3

3.2Vector quantization based-codeword histogram [13]

We generate a codebook of the signature containing codeword of size 4*4 pixel cluster and generate a codeword histogram which is used as a feature vector. The feature extracted for given signature is shown below.

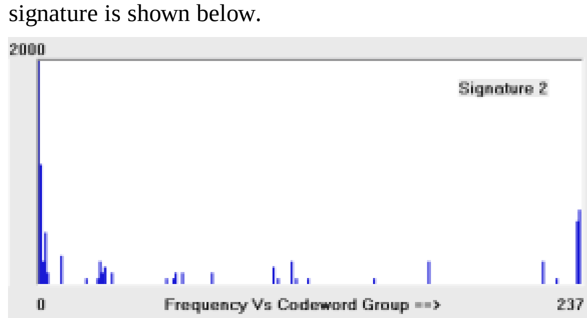

Figure 7 Codeword Histogram for Signature in Figure 3

3.3Grid, Texture features & Successive Geometric Centers

We modify the previously proposed features for our consider size as well as with new dimensions of the cluster. We use the Grid & Texture Information features [25] & successive geometric center with depth 2 (Two Iterations) [3]. Corresponding extracted feature set is shown in Figure 7 & 8. Figure 7. shows the grid information feature plot, with a block size of 10X10 Pixels, the texture information feature is a 2D matrix, as shown in Figure 8.

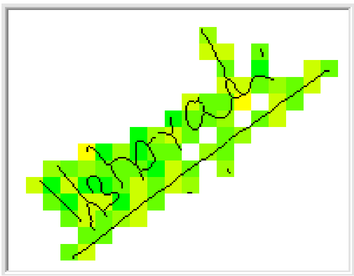

Figure 7 Representation of grid feature.

Successive geometric centers are calculated by recursively dividing the signature template at its geometric centers as method explained in [5]. We have used tow recursive iteration to get total 48 distinct feature points. The scheme and the feature vector are shown in Figure 9.

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8
p01	0	24	138	3	92	140	22	0
p11	0	10	32	0	9	29	8	0
p012	0	26	130	2	88	109	12	0
p112	0	4	39	1	13	60	18	0
p013	0	19	110	4	79	132	30	0
p113	0	11	59	1	22	41	1	0
p014	0	24	129	4	44	130	30	0
p114	0	6	38	1	52	41	1	0

Figure 8. Texture feature matrix for signature shown in Figure 2.

3.4Test Signature Database Generation

We have used a signature database consisting 984 signatures from 75 different persons. Per person 12 signatures are collected out of which 8 signatures are used for thresholds calculation and record creation. Remaining signatures are used as genuine test signatures. From some arbitrary persons we have collected forged signatures for testing purpose. We have collected 125 skilled forgery signatures, 30 casual or unskilled forgeries. Total number of signatures used for testing is 1139 at 600 dpi. Out of 1139 samples 480 signatures were used for user enrollment, 232 signatures were genuine test signatures, 127 skilled forgeries, 35 casual or unskilled forgeries, 250 un-enrolled users test signatures and 30 signatures were unusable due to distortion.

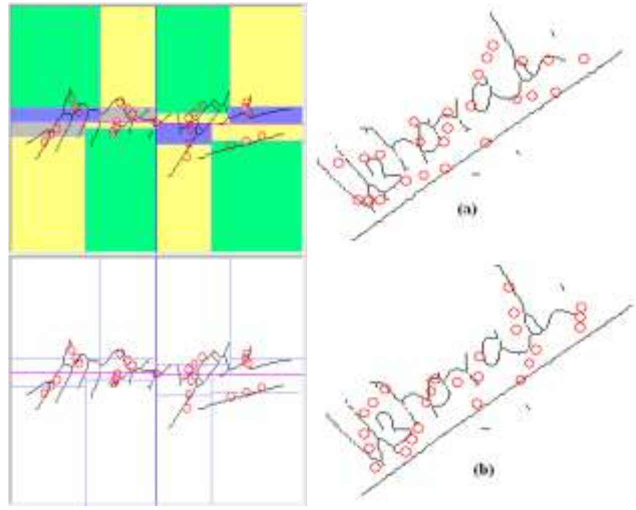

Figure 9. Feature points retrieved from signature template by vertical splitting of depth 2 (a) Horizontal Geometric centers (b) Vertical Geometric Centers

3.5Results

We have achieved accuracy up to 95%. The FAR-FRR plot is as follows, using this test bed we have performed total 353 tests for verification mode and 257 tests for recognition mode. The system is having decision threshold of 60% for both, the signature verification and signature recognition mode. Out of 353 verification tests 152 tests were for genuine signatures and 201 tests were for forged signatures. For the recognition mode we made 135 tests for genuine signatures and 122 tests were for forged signatures. Figure 10. shows **FAR-FRR** plot for signature recognition system for verification mode **At selected matching threshold level of 60 % we have achieved final FAR of the system as 2.5% and overall combined accuracy 95.08 % and the EER is 3.29%** in the verification mode**. In the recognition mode we have achieved accuracy of 93.08% and EER of 6%.**

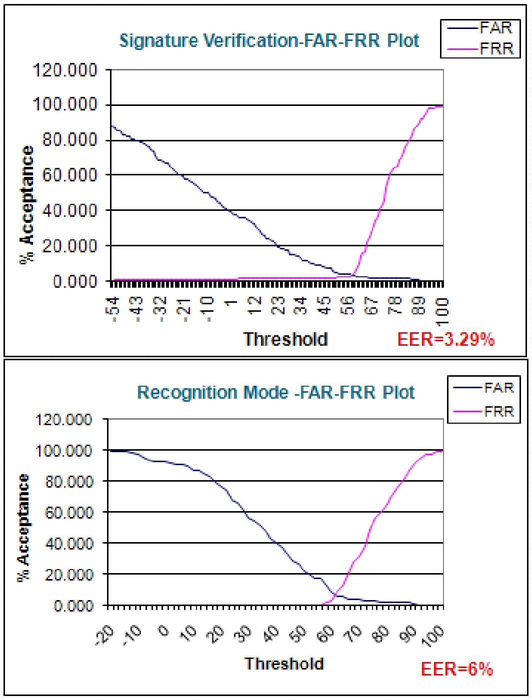

Figure 10. FAR-FRR plot for Signature Recognition System in Verification Mode (1:1) & Recognition Mode (1:N)

Table IV shows the individual performance metrics of the methods as well as for the final system. Table V shows the classified performance over different levels of forgeries.

Table IV

FAR FRR Reported by the Proposed System

Sr.	Feature	FAR	FRR
1	Walsh Coefficients	40%	42%
2	Vector Histogram	12%	22%
3	Grid Feature	8%	12%
4	Texture Feature	14%	20%
5	Final System	2.5%	6.5%

Table V

GroupWise Performance Metrics for Proposed System

Test Samples			Ratio	Result
All sample Signature s	Genuine		TAR	93.42
			FRR	06.58
	Forged	Casual	FAR	00.00
			TRR	100.00
		Skilled	FAR	05.60
			TRR	94.40

4.Conclusion

The paper gives in depth review of handwritten signature recognition systems and special consideration is given to the analysis of Static Signature Recognition Systems (SRS). The performance metrics of typical systems are compared along with their feature extraction mechanisms. We have discussed an off line SRS based conventional feature set as well as cluster based global features. This is a multi algorithmic system; such systems combine the advantages of individual feature sets and improve the Recognition rates. The system is has reported accuracy of 95.08% (CCR), which is higher than individual performance metrics.

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