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OSPCV: Off-line Signature Verification using Principal Component Variances

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Abstract: *Signature verification system is always the most sought after biometric verification system. Being a behavioral biometric feature which can always be imitated, the researcher faces a challenge in designing such a system, which has to counter intrapersonal and interpersonal variations. The paper presents a comprehensive way of off-line signature verification based on two features namely, the pixel density and the centre of gravity distance. The data processing consists of two parallel processes namely Signature training and Test signature analysis. Signature training involves extraction of features from the samples of database and Test signature analysis involves extraction of features from test signature and it's comparison with those of trained values from database. The features are analyzed using Principal Component Analysis (PCA). The proposed work provides a feasible result and a notable improvement over the existing systems.*

Keywords: *Biometrics, Centre of gravity distance, Off-line signature verification, Pixel density, Principal Component.*

I. Introduction

Identification of individuals is a very important aspect of security. The identification techniques opted may vary according to conveniences and requirements. The identification may be carried out by identity cards, pin codes, smart cards etc., but these are easily misused. A better way of individual identification is on a biological scale which is biometric verification. The biometric verification involves identification of individuals based on physiological and behavioral features. The physiological features include iris, face, finger print, DNA etc., and the behavioral features include voice, signature, gait which are unique to a person.

Signatures have been a primary method of identification of a person in all fields for purposes such as credit cards, contract agreements, cheques, wills, and other important documents. Thus a signature is widely used behavioral biometric for identifying a person. In day to day life millions of signatures need to be verified; this tends to be impossible by visual inspection and therefore an automated system is necessary for determining the authenticity of the signature. Several decades have witnessed intense research in the field of signature verification, especially in the Off-line signature verification. Signature verification is a process of discriminating between genuine and forged set of handwritten signatures and it is a difficult task as the signatures are a result of the physical and psychological status of an individual process.

Several techniques including different features of signature have been developed for the purpose of signature verification. The signature verification can be of two main types, the on-line or dynamic verification system and the off-line or static verification system. The main steps of signature verification system are preprocessing, thinning, feature extraction, and verification. Feature selection and extraction are fundamental processes in any verification system. The features used in the off-line signature verification are signature image area, length to width ratio, geometric centers, angle and distance of a pixel from a reference point, signature height and width. On-line signature verification system has features such as pen pressure, tilt, velocity, number of strokes required etc. The feature sets provide an ambiguous performance; hence signature verification has become a challenging task.

Off-line verification of signatures is done by considering an image of the signature which is obtained by using a scanner or a camera and extracting its features. Since the signature is scanned from a paper, it is considered as a static image. Off-line signature verification is difficult due to limited amount of features which can be extracted and the absence of dynamic features. Thus Off-line global and local features are extracted from the original signature and fed into the system and are later compared with test signatures using various comparison techniques such as Support Vector Machine, Neural Networks, Hidden Markov Models, Time warping, Principal Component Analysis (PCA) etc.

In the decision making phase, the forged images can be classified in three groups: (a) random, (b) simple, and (c) skilled. Random forgeries are formed without any knowledge of the signer‟s name and signature‟s shape. Simple forgeries are produced knowing the name of the signer but without having an example of signer‟s signature. Skilled forgeries are produced by people looking at an original instance of the signature, attempting to imitate as closely as possible. The disadvantages of on-line verification are : (i) heavy computational load and (ii) warping forgeries. The disadvantages of off-line verification are: (i) the signature can be easily forged as compare to on-line signature and (ii) features like pen pressure, and velocity cannot be acquired.

As mentioned earlier there are three important steps in signature verification; they are Preprocessing, Feature extraction and Data comparison. Preprocessing can be performed in various ways. Preprocessing is carried out to make the data extraction and the data verification process easier and efficient. The various preprocessing methods are binarization, background elimination, noise reduction, width normalization, thinning, rotation normalization, smoothing, and size normalization. The next process is the Feature extraction. Many local and global features are extracted from the preprocessed signature image and a database is created using the various learning and comparison techniques. Comparison is performed by extracting the features from the test signature and by comparing it with those of the originals using techniques such as correlation, analysis of variance, measuring Euclidean and Hamming distance etc,.

Motivation: Identities of individuals have been depicted and forged since times unknown. Previously the seals of kings and important people were forged and with advancement of time and technology, the modern biometric features are also prone to forgery. But the most misused of all the biometric features is the signature. Signatures are being widely used in the banking and legal purposes and this necessitates verification of thousands of signatures everyday which are used on cheques, wills, etc. This process by manual means is an unachievable task since the processing speed does not meet the demand and the security is diluted. This provides means for various types of fraudulent activities and has motivated to come up with an innovative off-line signature verification system.

Contribution: In this paper, Offline Signature Verification using Principal Component Variances is proposed. The system could be efficiently used for real time personal identification applications. The proposed OSPCV produces better Equal Error Rate by effectively differentiating between genuine and forgery signature samples. The algorithm overcomes the intra and inters signature variations and provides better Equal Error Rate (EER). Organization of the paper: The following sections hereon are organized as follows. The related work is presented in section II. We discuss about the background work in section III. The proposed signature verification model is described in section IV. The OSPCV algorithm is described in section V. The experimental results and the performance analysis are presented in section VI and the section VII contains the conclusion.

II. Related Work

Mustafa et al., [1] proposed an off-line signature verification system by considering four main features: Pixel density, Centre of gravity, Angle and Distance. The analysis is based on a technique called ANOVA (Analysis of Variance). The results also show that the combination of centre of gravity and pixel density features is the best for distinguishing between genuine and skilled forgeries.

Prakash and Guru, [2] developed a method for symbolic representation of off-line signatures based on relative distances between centroids. Distances between centroids of off-line signatures are used to form an interval valued symbolic feature vector for representing signatures. Similar signatures are clustered in each class and the cluster based symbolic representation for signature verification is also investigated.

Ismail et al., [3] proposed an off-line signature verification model using an Artificial Neural Network. Before the extraction of features, the pre-processing stage of noise removal and normalization is performed to prepare the signature so that the features can be extracted. The features which are extracted are moment features which are global shape characteristics described by moment, grey-scale co-occurrence matrices which are matrices of size N*N. When the size of the matrix is too large for direct use, measurements such as homogeneity, contrast, entropy and energy are used. The Principal Component Analysis is used for feature extraction and a database is created. The originality of the test signature is verified by making use of the Artificial Neural Network for comparison.

Blankers et al., [4] proposed that the participants were given the liberty of using two kinds of datasets that is off-line datasets that contained only the statistical data and the on-line datasets contained both statistical as well as the dynamic data hence a vast number of signatures were available for analysis. All the signatures were stored previously in the systems, the on-line files were saved as the text documents and the off-line files were saved as the PNG images. The markings for the teams were decided on the basis of the binary codes that is 0 for a wrong match and 1 for the correct match. and the programs used for evaluations were Linux or windows-win32 command line and the standards for declaration of the results were already preset by the NFI

(Netherlands Forensic Institute) on the basis of the EER (Equal Error Rate), FRR (False Rejection Ratio) and FAR (False Acceptance Ratio).

Vargas et al., [5] proposed a signature verification system based on analysis of pressure distribution in signature. The pixel density is more if the pressure is more and vice versa, the pressure feature is captured in form of pixel density. The technique used is called as Pseudo-Cepstral method. This method involves the calculation of histogram of grey scale image and used as spectrum for calculation of Pseudo-Cepstral coefficients. The Pseudo-Cepstral coefficients are used to estimate the unique minimum phase sequence. The sequence is used as feature vector for signature verification. The optimal or most desirable Pseudo-Cepstral coefficients are selected for best performance.

Ioana et al., [6] proposed an off-line signature verification model to extract a large number of features from the scanned signature and including a couple of new distance based features. First, the image is scanned and converted into a digital image and then edited to the dimension of 400*400 pixels. The noise is removed and the image is binarized and skeletonised. The features extracted are global features which are of the five main categories: extreme point position, number of pixels, histogram, pixel position and angular value. For classification they have first considered two methods namely the Naive Bayes method and the Multilayer Perceptron classifier. The Naive Bayes classifier is found to have more accuracy.

Vargas et al., [7] developed a system where in features representing the information of High Pressure Points from a handwritten signature image are analyzed for off-line verification. An approach for determining the high pressure threshold from grey scale images has been proposed. Two images are taken with one having the high pressure points extracted and the other being a binary version of the original signature. They are transformed to polar coordinates using which the pixel density ratio between them is calculated. The polar space is divided into angular and radial segments using which the local analysis of the high pressure distribution is done. Eventually two vectors having the density distribution ratio are calculated for nearest and farthest points from geometric centre of the original signature image. Experiments have been carried out using a database with

160 people‟s signatures. The accuracy of system for simple forgeries is tested with KNN and PNN. KNN stands for K-Nearest Neighbor, it is a technique to classify a new object by using its distances to the nearest neighboring training samples in the feature space. Probabilistic Neural Network (PNN) is a 3-layer, feed-forward, one pass training algorithm used for mapping and classifying the data.

Ismail et al., [8] have developed a method in which Fourier Descriptor and Chain Codes are used as features for representing the signature image. Chain codes represent a boundary by a connected sequence of straight-line segment of specified length and direction. Identification process is divided into two different sub-processes, they are recognition and verification. The recognition process employs the Principle Component Analysis and the verification process consists of a multilayer feed forward artificial neural network. Different distances are measured between the chain code feature vectors to evaluate the results of recognition process.

Chen and Srihari [9] proposed the use of embedded deformable template model based on the philosophy of the multi-resolution shape features, i.e., chain code processing and extrema extraction in order to reduce the problem involved in graph matching. This processing was done using threshold based binarization which was initially applied to the first image of the signature and chain code contour extraction was performed. Another technique used for the purpose was measuring deformation by point to point matching. This was performed by matching the end points of each of the letter in the reference signature. The thin-plate spline mapping using a deformation template model was introduced which used thin-plate splines for two dimensional interpolations. GSC (Gradient, Structural and Concavity) algorithm (Region Matching Version) was also developed in order to measure the image characteristics at different scales especially for multi resolutional signatures.

Emre et al., [10] proposed an off-line signature verification and recognition system based on global, directional and grid features of signatures. The comparison was done using Support Vector Machines (SVM). One against all approach is used for training signatures. The database consists of 1320 signatures taken from 40

persons. A total of 480 forged signatures are taken for testing. Testing is done in two different ways; verification and recognition. Verification stage involves the decision about whether the signature is genuine or forged. Recognition stage involves the process of finding the identification of the signature owner.

Banshider et al., [11] proposed a method using geometric centre approach for feature extraction. Euclidean distance model was used as parameters for classification of signatures. Threshold selection is based on average and standard deviations of the Euclidean distance. The method involves scanning the signature image, centering it and later extracting the feature points by horizontal and vertical splitting. For increasing the accuracy, especially in case of skilled forgeries, the split images or subparts are further split to smaller units which achieve better accuracy. Piyush et al., [12] proposed a signature verification system based on Dynamic Time Wrapping (DTW). The system involves extracting the vertical projection feature from the test signature image and then comparing it with the data set using elastic matching. The database used for the purpose consists of signatures of hundred persons. The system used consists of a modified discrete time wrapping algorithm which captures a 1-dimensional vertical projection.

Yacoubi et al., [13] proposed off-line signature verification based on Hidden Markov Model approach (HMM). The system automatically sets an optimal acceptation / rejection decision threshold for each signature. The experiment is carried out on two databases called as DB-I and DB-II. DB-I consists of 40 signers each contributing 40 signatures. The 40 signatures are divided into 2 groups; first group consists of 30 signatures used for training and next 10 signatures for testing. DB-II consists of 60 signers each contributing 40 signatures which are divided as above.

Simone et al., [14] initially worked on preprocessing work which involved operations like binarization, noise reduction, skew detection and character thinning and then the layout analysis was performed. Later on document analysis was done for performing the segmentation of documents. Pixel classification was initially applied to the binarization of document images. Region and Page classifications were also performed. Further improvements were done on the basis of the character segmentation which decomposed a sequence of characters into individual symbols which was performed by identifying touching characters and location of the cutting points. Analysis on OCR (Optical Character Recognition) and Word Recognition was performed for feature extraction and learning algorithms. The most important characteristic of the research was Time Delay Neural Networks which was used to deal with temporal sequences.

Robert et al., [15] proposed off-line signature verification based on directional Probability Density Function (PDF) and completely connected feed forward Neural Networks (NN). The experiment is conducted over a database containing 800 signature images signed by 20 individuals. The results were improved by using a rejection criterion. The threshold adjustments have to be carried out manually to get an acceptable global error rate and rejection rate.

Muhammad et al., [16] proposed off-line signature verification system based on a special type of transform called Contourlet Transform (CT). They suggested that Contourlet transform can be used in feature identification and feature extraction. The given signature was first pre-processed to remove noise and then was re-sized according to the requirements. The modified signature was used to get the unique features by applying a special form of Contourlet transform. The paper presents feature extraction based on Contourlet transform. This method is helpful to verify signatures of different languages which are closely related by alphabets. False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (ERR) are considered as important aspects of comparison and verification.

Stephane et al., [17] proposed that several steps are involved in verification of a signature which includes conversion of the data into a portable bit map, boundary extraction and feature extraction using MDF. Centroid feature was another important aspect inculcated in this research in which the signature was separated into two equal parts and center of gravity of each part was calculated. In order to increase the accuracy of the feature describing the surface area of any signature, triSurface feature was introduced. The length feature represented the length of the signature. Finally two neural classifiers were used namely the Resilient Back Propagation (RBP) neural network and the Radial Basis Function (RBF) neural network for the testing purposes.

Ye et al., [18] proposed an off-line signature verification system based on different scale wavelet transforms used in the curvature signature signals transformation. The system works in 3 main steps (i) extract the inflections of the signature curves using wavelet transform (ii) match the inflections of the template signature sequence with test signature sequence and divide signature into stokes (iii) match the corresponding strokes of the template signature sequence and the unknown signature sequence to arrive at the decision about originality or forgery. The database consists of 240 genuine signatures from 20 Chinese authors each contributing 12 signatures each. Six signatures are used for training purpose and the forged set consists of random and skilled forgeries.

Das et al., [19] tried to improvise on the problems in biometric methods by proposing an approach for off-line representation of the signatures. The application introduced was Directional Probability Density Function (PDF) and feed forward NN with back propagation learning to random signatures in the verification process. A number of methods were tried using the NN algorithm but the one that proved to be beneficial was the implementation of the PSO-NN algorithm. Particle Swarm Optimization (PSO) algorithm was executed by simulating social behavior among individuals and the NN structure provided a simple and effective way as a search algorithm. This research solved the problems based on optimization.

Oliveira et al., [20] brought a revolution in the writer specific approach of the off-line signature verification which was tedious and time consuming. Studies proved that ROC (Receiver Operating Characteristic) graphs were the required factor for the off-line verification. Thus Writer Independent Approach was introduced which was based on forensic document examination approach. The impacts of choosing different fusion strategies to combine the partial decision achieved by the SVM classifiers were analyzed and the experiments proved that the Max rule was more efficient than the original voting method proposed. Hence the Writer Independent Approach proved to be more efficient in comparison with the Writer Specific Approach.

Juan and Youbin [21] present an offline signature verification system based on pseudo-dynamic features both in writer-dependent and writer-independent mode. Features based on gray level are extracted using Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM) and histogram of oriented gradients. Writer-dependent SVM and Global Real Adaboost are used in classification.

Burcer et al., [22] designed a Conic Section Function Neural Network (CSFNN) for offline signature recognition. It is a framework for Multi-Layer Perceptron (MLP) and Radial Basic Function (RBF) networks. The CSFNN is trained by chip in the loop learning technique to compensate analog process variations. The recognition is performed on CSFNN hardware using two different signature datasets. Guerbai et al., [23] design an offline Handwritten Signature Verification System (HSVS). The curvelet transform and One-Class SVM (OC-SVM) are used conjointly for the genuine signature verification.

Gady and Suneel [24] Explore an approach for reducing the variability associated with matching signatures based on curve warping. It utilizes particle dynamics to minimize a cost function through an iterative solution of first-order differential equation and is evaluated by measuring the precision and recall rates of documents based on signature similarity. The Proposed approach can be used as a stand-alone system or preprocessing stage to better aligns signatures before applying the signature recognition techniques.

Saulo and Cleber [25] develop a neural network of Radial Basis Functions optimized by differential evolution algorithm with the features that discriminates between genuine signatures of simulated forgery. The proposed method is better than in [26]. Histograms and symbolic data can be incorporated to improve the performance.

Othman et al., [27] address the offline signature verification using artificial neural network approach. It addresses and compares various approaches and challenges to develop the verification system for secure services. A number of algorithms using ANN to address the issue of offline signature verification are evaluated.

III. Background

The comparison of various off-line signature verification methods are given in the Table 1. The brief explanation is as follows.

Shekar and Bharathi [28] propose an Eigen-signature: A Robust and an Efficient offline signature verification, Eigen and GLCM features model, consisting of two stages: preprocessing and Eigen-signature construction. The signature is preprocessed and Eigen signature is constructed. Then the image undergoes Signature recognition process which is computed using Euclidian distance. Database used is MUKOS explicitly for kannada, containing 1350 signatures from 30 individuals.

Mustafa et al., [29] propose an Offline Signature Verification using Classifier Combination of HOG and LBP Features. Database used is GPDS-300. The system performance is measured using the skilled forgery tests of the GPDS methods-160 signature dataset. The SVM is used as classifier.

Miguel et al., [30] propose a Robustness of Offline Signature Verification Based on Gray Level Features. Signature is acquired from MCYT and GPDS database, Check from Check database. Signature is preprocessed and Features are extracted and LBP, LDP and LDerivP are found. SVM and histogram oriented kernels or χ Kernel are used as a classifier.

Manoj and Puhan [31] investigate the trace transform based affine invariant features for offline signature verification. The features are obtained from a normalized associated circus function using trace and diametric functional. The affine relationship between intra-class and inter-class circus functions are converted to a simple scale and shift correspondence through normalization. The similarity measures for same-writer and different-writer pairs are used to decide the threshold. The proposed system is effective over a large unconstrained database.

Mujahed et al., [32] propose an Offline Handwritten Signature Verification System Using a Supervised Neural Network Approach based on back propagation algorithm. The results show accuracy, speed and throughput is better on comparison with the benchmark algorithms and consumes less time for choosing signature using available modern hardware.

Table 1: Comparison of various Off-line Signature Verification Methods

Author	Approaches	Database	Performance/Result	Advantages	Disadvantages
Shekar and Bharathi [28]	Eigen-signature and GLCM feature based algorithm	MUKOS	Suitable for 5 samples of any dimension feature vector	Used for Kannada offline signatures	Other state- of - art Approaches give better performance
Mustafa et al.,[29]	HOG and LBP Features	GPDS-300	LBP-Grid feature outperforms all other types	System does not require skilled forgeries of the enrolling user	Not work for alignment of two signatures and gradient magnitudes
Miguel et al., [30]	Gray Level Features	GPDS960 Gray Signature MCYT	LDerivP gives better result for all dimension feature vector	Used for Signatures on check	Processing requires blending of check and sign

Manoj and Puhan [31]	Trace Transform and circus functions	CEDAR	Receiver Operating Characteristics curve shows better result	possibility of design of new function	It cannot verify for more functional invariants
Mujahed et al., [32]	Neural Network Approach	Database with 900 signatures	Supervised learning is better than unsupervised learning	Signatures verification can be performed either offline or online	No specific Database is used
Prashanth et al., [34]	Geometric points, Standard Scores Correlation	GPDS 960 gray images database	Geometric points are compared using correlation	Simple and easy implementation	Geometric points alone are enough
Ramachandra et al., [35]	Cross Validation and Graph matching, Euclidean distance	GPDS960 gray images database	Geometric features are compared using Euclidean distance	Verification results are cross validated	Euclidean distance is inferior toother methods
Nguyen et al., [36]	Enhanced Modified Direction Feature, Neural Networks, Support Vector Machine	GPDS960 gray images database	Signature samples are trained by NN	Directional features are compared using NN	PCA outperforms EMDF and NN
Proposed OSPCV method	Pixel density „AND" Centre of Gravity distance, PCA	GPDS 960 gray images	The system is trained for intra signature variations	Efficient and error rate is lower	--

IV. System Model

In this section the definitions and the block diagram of Off-line Signature Verification by Analysis of Principal Component Variances (OSPCV) system are discussed.

Definitions:

i. Signature: It is a handwritten illustration of a person"s authentication depicted through lines and curves.
ii. False Accept Rate (FAR): The ratio of total number of forged signatures accepted to total number of signatures used for comparison.
iii. False Rejection Ratio (FRR): The ratio of total number of original signatures rejected to total number of signatures used for comparison.
iv. Equal Error Rate: It is the point of intersection of the FAR and FRR curves on the plot of FAR/FRR against Threshold. It can also be defined as the common threshold at which both FAR and FRR are equal.
v. Average Error Rate: It is the average of the FAR and the FRR at a common threshold.
vi. Pixel Density: It is defined as the number of black pixels pertaining to the signature in the cell of size 5*5 after splitting.
vii. Centre of gravity distance: It is the distance of the centre black pixel in the cell from the left hand bottom corner of the cell.

OSPCV System:

Fig.1 shows the block diagram of the OSPCV system. This system verifies the authenticity of the given signature of a person provided a set of genuine signatures are given for reference. The signature database consists of signatures from various individuals which are digitised by using a scanner. The pseudo dynamic features are considered for the comparison. These features are extracted by dividing the image into smaller cells, and each cell provides two features. The PCA tool is used for feature verification.

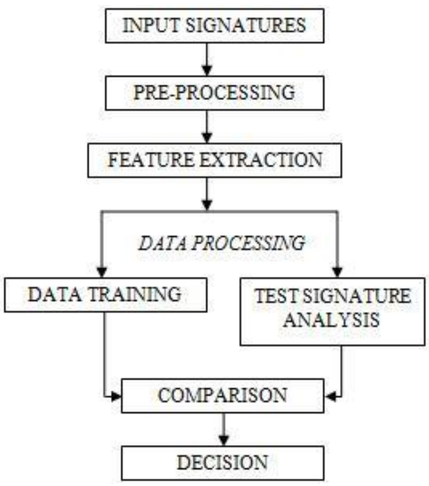
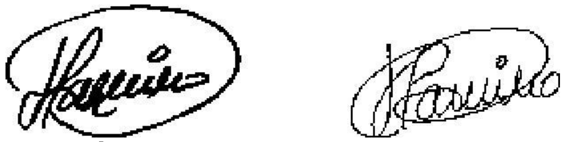


Fig .1. The block diagram of the OSPCV system.

1. Database: The Grupo de Procesado Digital de Senales (GPDS) database is used as input to the system. It consists of signatures from 960 individuals each having 24 genuine signatures and 30 forged signatures. The first one hundred individual‟s signatures are used for testing the algorithm. Sample original and forgery signals are as shown in Fig. 2.



Original signature Forged signature

Fig.2. GPDS database signature samples.

2. Pre-processing: The scanned signature image obtained is pre-processed. The pre-processing stage consists of the following steps: (i) The RGB image scanned is converted into a gray scale image and the intensities of pixels are normalised to range from 0 to 1; (ii) The image is passed through a Gaussian filter to eliminate any noise if present; (iii) The pixels whose intensity is less than 0.77 is made to have intensity 0 and others are made to have intensity 1. This is done in order to retain only the pseudo dynamic features such as the high pen pressure region; (iv) The boundaries of the signature are determined, and the parts which are not necessary are deleted; (v) The image is resized to 100*200; (vi) The resized image is then split into smaller cells of size 5*5. The idea is properly elaborated in the Fig. 3, which shows a window of size 5*5 slid across the entire image area, in other words the entire image is split into smaller cells of size 5*5 from each of which the features are extracted.

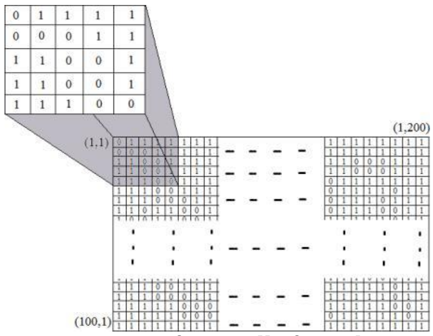


Fig.3. Extraction of 5*5 cells from the image.

3. Feature Extraction: The pre-processed signature image contains 800 smaller cells of size 5*5. Two features are extracted from each of the cells; they are pixel density and centre of gravity distance. Therefore we obtain 800 numbers of pixel density features and 800 number of centre of gravity distance features which gives a total of 1600 feature points. Extraction of pixel density feature: Pixels are extracted by counting the total number of black pixels present in an image cell. The Fig. 4 shows the cell which has been split from the signature image.

0	1	1	1	1
0	0	0	1	1
1	1	0	0	1
1	1	0	0	1
1	1	1	0	0

Fig.4. A 5x5 cell.

In this cell all the black pixels i.e., the pixels with intensity 0 are considered and the total number of black pixels is counted by using a counter in the program. The black pixels to be counted are shown darkened in Fig. 5, and the counting is done according to (1):

0	1	1	1	1
0	0	0	1	1
1	1	0	0	1
1	1	0	0	1
1	1	1	0	0

Fig.5. Cell showing the Black Pixels to be counted for Pixel Density.

If $\sum_{i=1}^{5}\sum_{j=1}^{5} I_s(i,j)=0$ then $Pa = Pa + 1$ ----- (1)

Extraction of centre of gravity distance features: The COG distance feature is extracted by dividing the total number of pixels in a cell by two and by taking the ceiling value of that number. This gives the centre of gravity of the cell; it is given by (2). The pixel at this count is considered and the position of this pixel is extracted. The coordinates of this pixel is used to find its distance from the left bottom corner of the cell. The Fig.6 illustrates the process and the same is represented in the formula in the (3):

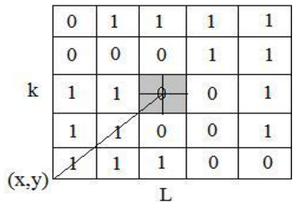


Fig.6. Process of finding the CoG distance.

$CoG = ceil \frac{Pd}{2}$ ----- (2)

$CoGdis = \sqrt{(k-x)^2 + (L-y)^2}$ ---------------- (3)

4. Data Processing: The pixel density and centre of gravity distance features are processed by Principal Component Analysis. The PCA concept is explained as follows.

4.1 Principal Component Analysis (PCA): It involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

It is used as a tool in exploratory data analysis and for making predictive models. PCA involves the calculation of the Eigen value decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centring of the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings. PCA is the simplest of the true eigenvector based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data.

4.1.1 Computing PCA using the covariance method

A detailed description of PCA using the covariance method is explained in the following section. The main aim of PCA is to convert a given data set X of dimension M to an alternative data set Y of smaller dimension L. So, we are to find the matrix Y, where Y is the Karhunen–Loève transform (KLT) of matrix X, it is shown in the (4):

$Y = KLT\ X$ ---- (4)

(a) Organizing the data set

Consider a data set of observations of M variables, which need to be reduced so that each observation can be described with only L variables, L < M. The data is arranged as a set of N data vectors $X_1, X_2, ...X_N$ with each X_N representing a single grouped observation of the M variables. $X_1, X_2, ...X_N$ are taken as column vectors, each of which has M rows. The column vectors are placed into a single matrix X of dimensions M × N.

(b) Calculation of the empirical mean

The empirical mean along each dimension $m = 1 M$ is found. The calculated mean values are placed into an empirical mean vector u of dimensions M × 1 and this is given by the (5):

$u_m = \frac{1}{N}\sum_{n=1}^{N} X[m,n]$ ------------------ (5)

(c) Calculation of the deviations from the mean

Mean subtraction is an integral part of the solution for finding a principal component as it minimizes the mean square error of the approximation of the data. When mean subtraction is not performed, the first principal component will correspond to the mean of the data. Hence it is absolutely necessary to perform mean subtraction (or "mean centering"), so that it ensures that the first principal component describes the direction of maximum variance, which can be used for the deciphering. Therefore the centering of data is performed by subtracting the empirical mean vector u from each column of the data matrix X. The mean-subtracted data is stored in the M × N matrix B, as given by the (6):

$$B = X - uh \qquad \text{----- (6)}$$

Where, h denotes a 1 x N row vector of all 1's, which is given in the form of (7):

$$h[n] = 1 \text{ for } n = 1 \ldots N \qquad \text{---- (7)}$$

(d) Finding the covariance matrix

The M × M empirical covariance matrix C is found by using the formula in (8):

$$C = E[B \otimes B] = E\, B \cdot B^{*} = \frac{1}{N} B \cdot B^{*} \qquad \text{---- (8)}$$

Where,

E denotes the expected value operator,

$\otimes$ denotes the outer product operator, and

$*$ denotes the conjugate transpose operator.

(e) Find the eigenvectors and Eigen values of the covariance matrix

The matrix V of eigenvectors which diagonalizes the covariance matrix C is calculated using the (9):

$$V^{-1} C V = D \qquad \text{---- (9)}$$

D is the diagonal matrix which has the eigenvalues of C. The Matrix D will take the form of an M × M diagonal matrix, where:

$$D[p,q] = \lambda_m \text{ for } p = q = m \qquad \text{---- (10)}$$

The (10) is the mth Eigen value of the covariance matrix C, and (11):

$$D[p,q] = 0 \text{ for } p \neq q \qquad \text{---- (11)}$$

Matrix V, is also of dimensions M × M, containing M column vectors, each of length M, which represent the M eigenvectors of the covariance matrix C. The Eigen values and eigenvectors so obtained are ordered and paired. Thus the mth Eigen value corresponds to the mth eigenvector.

(f) Rearranging the Eigenvectors and Eigen values

The columns of the eigenvector matrix V and Eigen value matrix D are sorted in the order of decreasing Eigen value, to make sure that the first principal component has the maximum variation.

(g) Computation of the cumulative energy content for each Eigenvector

The Eigen values denote the distribution of the energy of source data among each of the eigenvectors, where the eigenvectors form a basis for the data. The sum of the energy content across all of the Eigen values from 1 through m is the cumulative energy content g for the mth eigenvector. It is as shown in the (12):

$$g\, m = {}_{q=1}{}^{m} D[q,q] \qquad \text{for } m = 1 \ldots M \qquad \text{-----(12)}$$

(h) Selection of a subset of the eigenvectors as basis vectors

The first L columns of V are saved as the M × L matrix W, this is illustrated in (13):

$$W[p,q] = V[p,q] \text{ for } p = 1 \ldots M,\ q = 1 \ldots L \qquad \text{---- (13)}$$

Where $1 \leq L \leq M$

The vector g is used as a guide in choosing an appropriate value for L. The aim is to choose a value of L as small as possible while achieving a reasonably high value of g on a percentage basis. For example, L may be chosen so that the cumulative energy g is above a certain threshold, like 90 percent. In this case, the smallest value of L is chosen such that (14) is satisfied:

$$g[m = l] \geq 90\% \text{------------} \quad (14)$$

(i) Convert the source data to z-scores

An M*1 empirical standard deviation vector S is created from the square root of each element along the main diagonal of the covariance matrix C, as given in (15):

$$S=\{s[m]\} = \overline{} \; C\,p,q\,, \text{ for } p = q = m = 1 \ldots . M \text{--------------} \quad (15)$$

The M x N z-score matrix is calculated by using the (16); it should be made sure that the division is performed element-by-element. While this step is useful for various applications as it normalizes the data set with respect to its variance, it is not integral part of PCA/KLT:

$$Z = \frac{B}{S.h} \text{--------------------------} \quad (16)$$

(j) Project the z-scores of the data onto the new basis

The projected vectors are the columns of the matrix given by the (17):

$$Y=W^{*}.Z=KLT\{X\} \text{-----------} \quad (17)$$

Where W^{*} is the conjugate transpose of the eigenvector matrix. And the columns of matrix Y represent the Karhunen– Loève transform (KLT) of the data vectors present in the columns of matrix X .

(k) Derivation of PCA using the covariance method

Consider X to be a d-dimensional random vector expressed as column vector. Without losing generality, assume X has zero mean. We need to find a $d * d$ orthonormal transformation matrix P such that (18) is satisfied, with the constraint that $\operatorname{cov}(Y)$ is a diagonal matrix and $P^{-1} = P^{T}$:

$$Y = P^{T}X \text{------------} \quad (18)$$

By substitution, and matrix algebra, we obtain (19), which is further simplified to obtain (20).

$$\begin{aligned} \operatorname{Cov}(Y) &= E[YY^{T}] \quad \text{---------------} (19) \\ &= E[(P^{T}X)(P^{T}X)^{T}] \\ &= E[(P^{T}X)(X^{T}P)] \\ &= P^{T}E[XX^{T}]P \\ &= P^{T}\operatorname{cov}(X)P \end{aligned}$$

We now have

$$\begin{aligned} P\operatorname{cov}(Y) &= PP^{T}\operatorname{cov}(X)P \\ &= \operatorname{cov}(X)P \end{aligned} \quad \text{----------}(20)$$

P is rewritten as d number of d x 1 column vectors, so

$$P = [\, P_1,P_2,\ldots,P_d] \text{------------} \quad (21)$$

and cov(Y) as

$$\begin{matrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_d \end{matrix} \text{------------} \quad (22)$$

Substituting (21) and (22) into (20), we obtain (23).

$$[\lambda_1 P_1, \lambda_2 P_2 \ldots . \lambda_d P_d] = [\operatorname{cov}(X)P_1, \operatorname{cov}(X)P_2, \ldots, \operatorname{cov}(X)P_d] \text{-----------------} \quad (23)$$

It is noted that in $\lambda_i P_i = \operatorname{cov}(X)P_i$. P_i is an eigenvector of the covariance matrix of X. Thus, by finding the eigenvectors of the covariance matrix of X, we find a projection matrix P that satisfies the original constraints.

The data analysis by PCA consists of two stages. They are: (i) Signature training and (ii) Test signature analysis by PCA, which is explained as follows.

(i) Signature training: In this process eight original signatures are taken and divided into two different groups of four each, named as M and N. The M group signatures are considered as reference signatures. The features extracted from the signatures are analysed separately. The pixel density features of the M group signatures are arranged in a matrix A with each signature representing a column. The N group signatures are taken one at a time and its features are inserted as the last column in the matrix A. The principal components of the matrix A are found. The variances of the principal components and the cumulative sum of the variances are found. The first value in the cumulative sum array is stored in another matrix B. The same process is performed for the other 3 signatures of group N and the array B is filled in. The average of the array B is found and the threshold value is added to the truncated value of the average. This forms the ideal comparison value (I) for the OSPCV system. The process is repeated for the centre of gravity feature also.

(ii) Test Signature Analysis: The pixel density features of the M group signatures are arranged in a matrix T with each signature representing a column. The test signature‟s features are inserted as last column in the matrix T. The principal components of the matrix T are found. The variances of the principal components and the cumulative sum of the variances are found. The first value in the cumulative sum array (K) is the value to be compared with the ideal comparison value (I). The process is repeated for the centre of gravity feature also.

V. Comparison and Decision

The variances are represented by the energy of the Principal Components accounted for by its Eigen values. Thus if principal component has more energy then it belongs to same group. Hence the values K and I are compared as follows: If $K < I$ which means that if the test signature has less energy than the reference signatures then the signature is forged else if $K >= I$ which means the energy of test signature is more than reference signature then the signature is genuine.

VI. OSPCV Algorithm

Problem definition:

Given a signature whose authenticity is to be verified, the goal is to:

(i) Pre-process the obtained signatures.

(ii) Extract the centre of gravity distance and the pixel density features.

(iii) Test the authenticity of the test signature by using Principal Component Variances.

Table 1 shows the algorithm for the proposed system known as the OSPCV, which verifies the authenticity of a given test signature. Digitising the test signature and the genuine signature database is done using a scanner. The signature is pre-processed as per the steps shown in the algorithm. The image is split into smaller cells and features are extracted from each cell. The features are fed into PCA to obtain the similarities of the signature. And the decision is made based on similarities between genuine and test signatures.

Table 1: OSPCV Algorithm

Input: Database of genuine and forgery signatures. **Output:** Decision stating matching or not matching. **(i)** Acquire the signature images from the database chosen as well as the test signature. **(ii)** The RGB images are converted to gray scale images. Only the exact signature area is considered for further processing. Noise removal, thinning are performed. **(iii)** The image obtained from the previous stage is resized to 100x200 and split into smaller cells of size 5*5. **(iv)** The pixel density and centre of gravity distance features are extracted from each of the cells. **(v)** The extracted features are processed using the PCA. **(vi)** The value obtained from PCA for the test signature and the database are compared. **(vii)** The decision is made on the basis of relation between the first value in the cumulative sum array (K) and the ideal comparison value (I).

VII. Experimental Results and Performance Analysis

The experiment is carried out on the GPDS960 database [33], which consists of signatures from 100 individuals each having 24 genuine signatures and 30 forged signatures which amount to a total of 6400 signatures having 2400 genuine and 3000 forged signatures. All the images are resized to 100*200. The programming software used for execution of the proposed algorithm is the MATLAB.

Table 2: FAR and FRR vs. the Threshold values for the PD, CoG distance, PD OR CoG distance and PD AND Centre of Gravity distance feature for GPDS database [100x200]

Threshold	Pixel Density (PD)		Centre of Gravity distance		PD OR CoG distance		PD AND CoG distance	
	FAR	FRR	FAR	FRR	FAR	FRR	FAR	FRR
-5	84.18	1.6	80.76	0.42	88.8	1.6	76.15	0.42
-4	71.53	4.16	66.83	2.02	77.6	4.7	60.76	1.49
-3	56.49	8.65	51.36	4.8	63.07	9.4	44.78	4.05
-2	38.97	15.38	33.41	11.85	44.7	17.2	27.69	10.04
-1	23.58	25.42	18.03	21.58	27.52	27.99	15.1	19.01
0	12.05	39.42	9.14	37.82	15.55	43.8	5.64	33.44
1	4.27	53.09	3.33	54.48	5.55	60.47	2.05	47.11
2	1.45	64.95	0.76	68.91	1.88	71.79	0.34	62.07
3	0.34	75.32	0.17	77.77	0.42	80.02	0.08	73.07
4	0.08	82.26	0	82.37	0.08	84.72	0	79.91
5	0	86.32	0	84.5	0	87.28	0	83.54

TABLE 2 shows variation of FAR and FRR with threshold values for the case of Pixel Density (PD), centre of gravity distance, PD OR CoG distance and PD AND CoG distance features. The threshold is varied from -5 to +5 and the corresponding FAR and FRR are tabulated. It can be seen that FAR and FRR vary inversely, that is an increase in FAR means decrease in FRR and vice versa. An optimum threshold is chosen such that both FAR and FRR are in permissible limits. Experimental results have shown that optimum FAR and FRR are obtained when threshold lies in range of -2 to 0.

The four graphs of FAR and FRR against threshold in case of GPDS database obtained for four different features are shown in Figure 7. As threshold increases, the value of FRR increases and FAR decreases. The value of EER obtained for pixel density and center of gravity distance features is 24.07 and 20.2 respectively for optimal threshold of -1.0722 and - 1.141 at a point where FAR equals to FRR. The PD and CoG distance features are fused by logical operations OR and AND. The corresponding graphs are also shown in the Fig.7. It is found that the value of EER is 27.81 and 17.06 for OR and AND operations respectively at optimal threshold of -1.01 and -1.217.

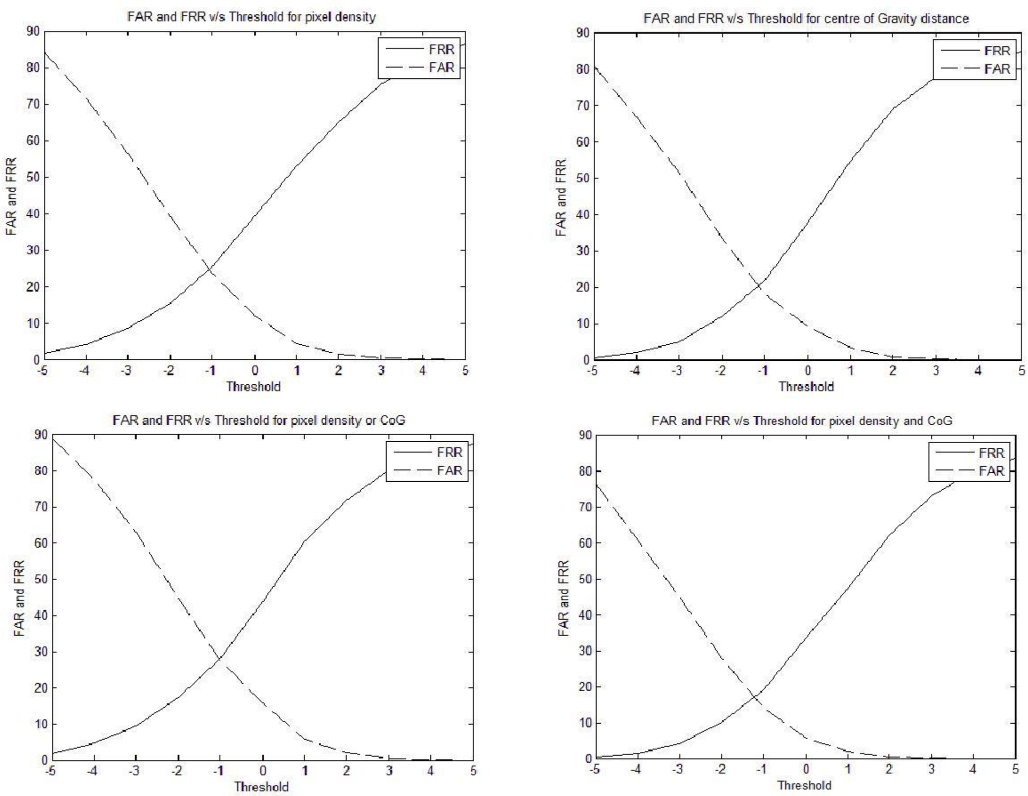


Fig.7. FAR/FRR against Threshold plot for Pixel density, Centre of Gravity distance, PD OR CoG distance and PD and CoG distance features for GPDS database [100x200]

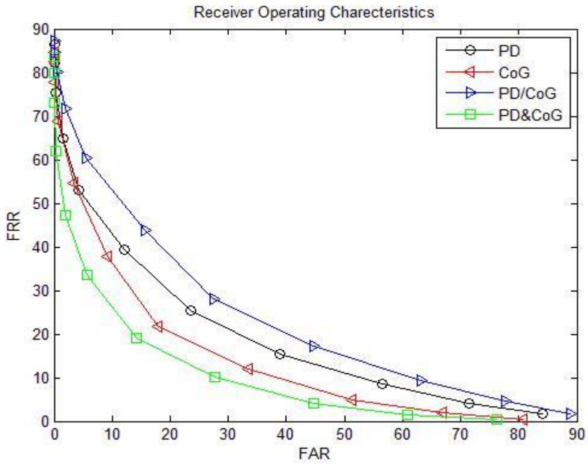


Fig.8. Receiver Operating Characteristics of OSPCV system.

The Receiver Operating Characteristics for different features of OSPCV system is shown in Fig.8. The ROC consists of plot of FRR versus FAR for the features of pixel density, centre of gravity distance, pixel density OR centre of gravity distance, and pixel density AND centre of gravity distance. The graph shows that system performance for pixel density AND centre of gravity distance is better than other cases.

Table 3 shows the comparison of performance of the OSPCV model with other contributions, which have used the same GPDS database and it shows a notable improvement when compared to those systems.

Table 3. Comparison of EER values of the proposed model with the existing models for GPDS database.

Reference	Method	% EER
Prashanth et al., [34] (SSCOSV)	Pixel density and geometric points, Standard Scores Correlation	30.04
Ramachandra et al., [35] (SCGMC)	Cross Validation and Graph matching, Euclidean distance	24.0
Nguyen et al., [36]	Enhanced Modified Direction Feature, Neural Networks, Support Vector Machine	20.07
Proposed OSVPCV method	Pixel density „AND" Centre of Gravity distance, Analysis of Principal Component Variances	**17.06**

The graphical comparison of percentage EER values of the proposed OSPCV with pixel density AND centre of gravity distance feature with publically reported results on the GPDS database is shown in the Fig.9. The figure shows that the performance of the proposed system is better than others [26, 27, 28] using the GPDS database.

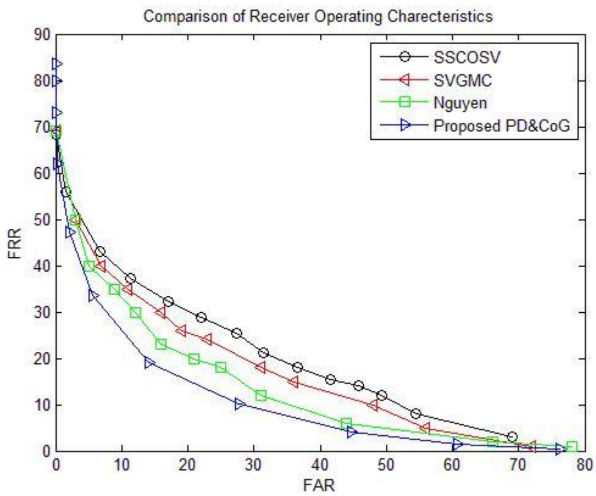


Fig.9. Comparison of Receiver Operating Characteristics of the proposed OSPCV system with other methods.

VIII. Conclusions

In this paper, Off-line Signature Verification using Principal Component Variances is presented. In signature verification process, two problems are encountered. They are intra-person variations (variations of the same person‟s signature taken at different time instances), and inter-person variations (variations between the same signatures signed by two different people). Both the problems have to be successfully counterbalanced by the system. The proposed system uses Pixel density and Centre of gravity distance features for representing the signature image and the Principal Component Variances to analyse the features and arrive at a suitable solution for verifying signatures. All experimental results have demonstrated that the proposed method achieves high performance. Hence we conclude that the proposed system can be used effectively for Off-line Signature Verification purpose with great reliability as it gives minimum error compared to existing systems.

Since we have developed our own technique for incorporating the PCA, we reckon that this algorithm can be effectively extended to other areas of biometric verifications like the Face recognition, Retina Identification, Fingerprint verification with small modifications. The performance of the system can further be improved by fusing the current technique with other techniques such as SVM and Neural Networks.

References

[1]. Mustafa Agil Muhamad Balbed, Sharifah mumtazah Syed Ahmad, and Asma Shakil, "ANOVA-Based feature Analysis and Selection in HMM based Off-line Signature Verification System," IEEE Conference on Innovative Technologies in Intelligent Systems and Industrial Applications, pp. 66-69, 2009.

[2]. H. N Prakash and D S. Guru, "Geometric Centroids and their Relative Distances for Off-line Signature Verification," IEEE International Conference on Document Analysis and Recognition, pp. 121-125, 2009.

[3]. A Ismail, M A Ramadan, T El Danf, and A H Samak, "Automatic Signature Recognition and Verification using Principal Components Analysis," IEEE International Conference on Computer Graphics, Imaging and Visualisation, pp. 356-361, 2009.

[4]. V. L Blankers, C. E. Van den Heuvel, K. Y Franke and L G. Vuurpijl, "The ICDAR 2009 Signature Verification Competition," International Conference on Document Analysis and Reorganization, pp. 1403 - 1407, 2009.

[5]. Jesus F. Vargas, Miguel A, Carlos M Travieso, and Jesus B Alonso, "Off-line Signature Verification System based on Pseudo-Cepstral Coefficients" International Conference on Document Analysis and Recognition, pp. 126-130, 2009.

[6]. Ioana Barbantan, Camelia Vidrighin, Raluca Borca, "An Off-line System for Handwritten Signature Recognition," IEEE Interntional Coneference on Intelligent Computer Communication and Processing, pp. 3 -10, 2009.

[7]. J Francisco Vargas, Miguel A Ferrer, Carlos M Travieso and Jesus B Alonso, "Off-line Signature Verification based on High Pressure Polar Distribution," International Conference on Frontiers in Handwritting Recognition, pp. 373-378, 2008.

[8]. Ismail A Ismail, Mohamed A Ramadan, Talaat S El-Danaf and Ahmed H Samak, "An Efficient Off-line Signature Identification Method based on Fourier Descriptor and Chain Codes," International Journal of Computer Science and Network Security, Vol. 10, No.5, pp.29-35, 2010.

[9]. Siyuan Chen and Sargur Srihari, "A New Off-line Signature Verification method based on Graph Matching," International Conference on Pattern Recognition, pp. 869-872, 2009.

[10]. Emre Ozgunduz, Tulin Şentrk and M Elif Karslıgil, "Off-line Signature Verification and Recognition by Support Vector Machine," European Signal Processing Conference, pp. 1-6, 2005.

[11]. Banshider Majhi, Y Santhosh Reddy, and D Prasanna Babu, "Novel Features for Off-line Signature Verification," International Journal of Computers, Communications and Control, vol. 1, no. 1, pp. 17-24, 2006.

[12]. A Piyush Shanker and A N Rajagopalan, "Off-line Signature Verification using DTW," Pattern Recognition Letters, vol. 28, no. 12, pp 1407-1414, 2007.

[13]. A El-Yacoubi, E J R Justino, R Sabourin, and E Bortolozzi, "Off-line signature verification using HMMs and Cross validations," IEEE Signal Processing Society Workshop, pp 859-868, 2000.

[14]. Simone Marinai, Marco Gori and Giovanni Soda, "Artificial Neural Networks for Document Analysis and Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 1, pp.23-35, 2005.

[15]. Robert Sabourin, Jean Pierre Drouhard, "Off-line Signature Verification System using Directional PDF and Neural Networks," International Conference on Pattern Recognition Methodology and Systems, pp 321-325, 1992.

[16]. Muhammad Reza Pourshahabi, Mohamad Hoseyn Sigari, and Hamid Reza Pourreza," Off-line Hand Written Signature Identification and Verification using Contourlet Transform," IEEE International Conference of Soft Computing and Pattern Recognition, pp. 670-673, 2009.

[17]. Stephane Armand, Michael Blumenstein, and Vallipuram Muthukkumarasmy, "Off-line Signature Verification based on the Modified Direction Feature," International Conference on Pattern Recognition, pp. 509-512, 2006.

[18]. Xiufen Ye, Weiping Hou, and Weixing Feng, "Off-line Handwritten Signature Verification with Inflections Feature," International Conference on Mechatronics and Automation, pp 787-792, 2005.

[19]. M Taylan Das and L Canan Dulger, "Off-line Signature Verification with PSO-NN Algorithm," International Symposium on Computer and Information Science, pp.1-6, 2007.

[20]. Luiz S Oliveira, Edson Justino, and Robert Sabourin, "Off-line Signature Verification using Writer-Independent Approach," International Joint Conference on Neural Networks, pp. 2539-2544, 2007.

[21]. Juan Hu and Youbin Chen, "Offline Signature Verification Using Real Adaboost Classifier Combination of Pseudo-dynamic Features," 12th International Conference on Document Analysis and Recognition, pp.1345-1349, 2013.

[22]. Burcer Erkman, Nihan Kahraman, Revna Acar Viral, and Tulay Yildirin, "Conic Section Function Neural Network Circuitry For Offline Signature Recognition," IEEE Transactions on Neural Networks, vol. 21, no. 4, pp. 667-672 April 2010.

[23]. Y Guerbai, Y Chibani and B Hadjadji, "Writer-Independent Handwritten Signature Verification based on One-Class SVM Classifier," International Joint Conference on Neural Networks, pp. 327-331, 2014.

[24]. Gady Agam and Suneel Suresh, "Warping-Based Offline Signature Recognition," IEEE Transactions on Information Forensics and Security, vol. 2, no. 3, pp. 430-437, September 2007.

[25]. Saulo Henrique Leoncio de Medioros Naploes, Cleber Zanchettin, "Offline Handwritten Signature Verification through Network Radial Basis Functions Optimized by Differential Evolution," IEEE World Congress on Computational Intelligence, pp. 10-15, June 2012

[26]. Vargas J. F, Ferrer, M. A. Travieso, C. M. Alonso J. B., "Offline Signature Verification based on Gray Level Information using Texture Features," Pattern Recognition , ISSN: 0031-320,vol. 44, no. 2, pp. 1037-1045, 2010.

[27]. Othman o-khalifa, Md. Khorshed Alam, Aisha Hassan Abdalla, "An Evaluation on Offline Signature Verification using Artificial Neural Network Approach," International Conference On Computing, Electrical And Electronic Engineering (ICCEEE), pp. 36 8-371, 2013.

[28]. B. H. Shekar and R. K. Bharathi, "Eigen-signature: A Robust and an Efficient Offline Signature Verification Algorithm," IEEE-International Conference on Recent Trends in Information Technology, pp. 134-138, June 2011.

[29]. Mustafa Berkay Yilmaz, Berrin Yanikoglu, Caglar Tirkaz and Alisher Kholmatov, "Offline Signature Verification using Classifier Combination of HOG and LBP Features," IEEE International conference of Biometrics, pp. 1-7, 2011.

[30]. Miguel A. Ferrer, J. Francisco Vargas, Aythami Morales, and Aarón Ordóñez "Robustness of Offline Signature Verification Based on Gray Level Features," IEEE Transactions on Information Forensics and Security, vol. 7, no. 3, pp. 966 -977, June 2012.

[31]. M. Manoj Kumar and N. B. Puhan, "Offline Signature Verification using the Trace Transform," IEEE International Advance Computing Conference, pp. 1066-1070, 2014.

[32]. Mujahed Jarad, Nijad Al-Najdawi and Sara Tedmori "Offline Handwritten Signature Verification System using a Supervised Neural Network Approach," International Conference on Computer Science and Information Technology, pp. 189-195, 2014.

[33]. M. Blumenstein, Miguel A. Ferrer and J. F. Vargas, "Off-line Signature Verification Competition: Scenario2," International Conference on Frontiers in Handwriting Recognition, pp. 721-726, 2010.

[34]. Prashanth C. R, K. B. Raja, K. R. Venugopal, and L. M. Patnaik, "Standard Scores Correlation based Off-line Signature Verification System," IEEE Conference on Advances in Computing, Control and Telecommunication Technologies, pp. 49 -53, 2009.

[35]. Ramachandra A. C, Ravi J, K. B. Raja, Venugopal K R.. and L M. Patnaik, "Signature Verification using Graph Matching and Cross-Validation Principle," ACEEE International Journal of Recent Trends in Engineering, vol. 1, no. 1, pp. 57-61, 2009.

[36]. Vu Nguyen, Michael Blumenstein, Vallipuram Muthukkumarasamy and Graham Leedham, "Off-line Signature Verification using Enhanced Modified Direction Features in Conjunction with Neural Classifiers and Support Vector Machines," IEEE International Conference on Document Analysis and Recognition, vol. 2, pp. 734-738, 2007.

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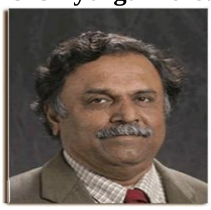

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