MANGALORE UNIVERSITY

Final-Synopsis

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TITLE OF THE WORK
E-PAS: Efficient Algorithms for Person Authentication based on Signature Biometric

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E-PAS: Efficient Algorithms for Offline Signature Verification based on Signature Biometric.

1.1 Introduction

The term Bio-metric is derived from Greek words bio means life and metric means measure. Biometric possess distinct characteristics from one person to another which helps to distinguish. As these traits cannot be stolen, lost or forgotten so they can play a significant role for better representation of an individual. Biometrics can be used to replace traditional authentication methods such as PIN number, passwords or pattern matching. When biometric emerged as strong authenticating metric to authenticate a person, automated verification systems are developed to verify as well as to identify the biometrics of a person. The significant research work in the area of Machine Learning and Computer Vision has influenced lot of advances in application areas such as medical image processing, satellite image processing (hyper spectral image), industries, traffic control system, Internet of Things (IoT), academics and office administration. Biometrics technology could be more appropriate among these application areas where human characteristic will be the key factor to identify or verify an individual human. With respect to biometrics the human characteristics are categorized in to two, one is behavioral and another is physiological. Under behavioral biometrics category signature, gait and voice biometric comes. And under physiological biometrics face, palm, iris, finger or thumb print and DNA sequence comes which is shown in figure 1.

Signature is one of the most accepted behavioural biometric attribute in the society as a means of authentication and identification of an individual. Each signer writes their signature uniquely, this helps to distinguish one signature from another. Due to this unique nature, from several decades people tend to use their signature in their day to day transactions, in administration and also in the sector of commerce. People by signing make the documents more authenticate and legal. In these applications there is a chance of forging the signature of someone by another to get the benefits. In order to verify the genuineness of a signature and also to authenticate individual person based on their signature, biometric based signature verification system can be used. Signature verification has various applications namely authentication of cheque, certificates, financial bonds, agreement notes, Office documents, notifications and letters etc.

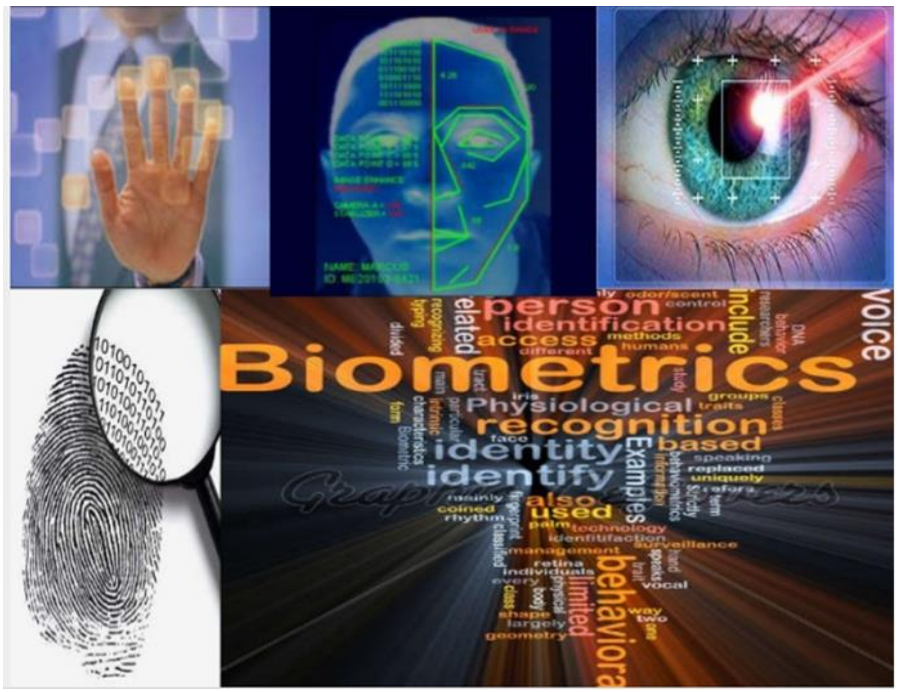

Figure 1. Diagrammatic representation of Biometrics.

A forge signature is one that is imitation of signature done by a fake signer. There are three types of forge signatures namely skilled, random and simple forgery. In skilled forgery the forger observes and analyses the original signature. Further forger practices the way of writing the original as accurate as possible for a while then forges. In simple forgery the forger knows the pattern of signature and then try to write same pattern without practice. In case of random forgery the forger does not know the pattern of original signature, but writes based on the guess or assumption.

Handwritten signature verification is of two types one is Off-line Signature Verification and another is On-line Signature Verification. The signature acquisition method is the main difference between offline and online signature verification. In Off-line Signature Verification signature samples are collected from a signer on a paper and the scanned copy of this paper is fed for verification process, where it employs various image processing techniques to verify whether the signature is genuine or forge. It's also known as Static Signature Verification. In case of On-line Signature Verification, the signer is allowed to write their signature on a sensor based surface of digital gadgets like scanner, pen tablet etc. and then performs several image processing operations for signature verification. It's also known as Dynamic Signature Verification. In both types various image processing techniques employed at various stages to perform pre-processing, feature extraction and classification. These two types are briefly explained below.

Applications of Biometric Signatures:

- Biometric signatures are used in banking and finance industry in order to restrict duplicate signature frauds.
- Dynamic signature verification technology is used, where paperless procedures are involved. For instance, in case of online insurance buying or online application submission for job recruitments.
- Patient records and medical prescriptions can also be protected using biometric signature recognition. Different options of hospital application portal log-in can be done using signature as a replacement of password.
- Various government offices and defence organizations make use of this technology to prevent the unauthorized access to sensitive data as well as for user identification.
- Computers at homes as well as organizations are protected against illegitimate access using biometric signature recognition.
- In most recent application field, biometric technology is a security measure, installation is available in smart phones to prevent unauthorized access, which is very useful to protect the user data when the device is lost or stolen.

Advantages of Signatures as a biometric:

- No forgery of biometric signatures is possible, as it involves distinct writing styles of different individuals.
- Encryption and decryption algorithms are used to create the templates for different user signatures and these algorithms are difficult to break by intruders.

- Data stored inside pocket PCs and smartphones can be protected with the help of dynamic signature verification.
- Easy to employ and low-cost technology, with limited requirements of special hardware.
- Eliminates the headache of remembering PIN and passwords to access different systems.
- Signature based identification is a process already familiar in the society and it is much accepted technology by the public and thus, biometric signature recognition is easy to understand and adopt
- Dynamic signature verification is the technology, designed to effectively cater the contemporary security needs.

Challenges in Signature Verification:

There are two types of challenges encountered in signature verification, namely inter-class variation and intra-class variation. Inter-class variation poses great treat to any signature verification system where different individuals try to forge the original, successful individual causes huge damage depends on the application where signature involved. Intra-class variation involves the same person writes their signature with slight variations due to old age or ill-health. It also happen when the person is under pressure during writing a signature. It is difficult to classify the signature whether forge or original in intra-class variation as same as in case of skilled forgery detection.

Motivation to take-up this research problem:

Some of the following challenges motivated us to take up the work. There are several challenges in building an efficient offline signature verification system. Some of technically challenging aspects for building an offline Signature verification system are:

- Direction vector cannot be obtained from offline signatures.
- Offline signature is digitized by scanning which introduces sampling and quantization noise. Background of signature is not always white. Hence segmenting the signature is a challenge.
- Signature dimension varies from one instance to another.
- Inclination angle varies from one instance to another.
- Non-availability of dynamic features. i.e dynamic information can’t be recorded.
- Limited number of signature sample per signer is available.
- High intra-class variability leads to erroneous results.

1.2 Phases of Off-line Signature Verification System: An Overview

It undergoes different phases namely Data Acquisition, Data Pre-Processing, Feature Extraction, Classification and lastly Performance evaluation. The general diagrammatic representation of offline signature verification system is shown in the figure 2.

1.2.1 Data Acquisition

Signature samples are collected from signers on white plain paper in black or blue ball point pen. Further the scan copy of these papers are fed for signature verification process. Several signature database are publically available for research purpose. The popular databases publically available are CEDAR, GPDS, and ICDAR 2009.

1.2.2 Data Pre-Processing

The collected data samples are raw by nature and which may contain noise, redundant area, unsuitable colour, high scale etc. So which may not be suitable to process for verification. It's necessary to apply several pre-processing technique to make data samples suitable to process. Pre-processing greatly helps in efficient extraction of desired features so that improve the performance of the model. It also reduces computational cost in classification. Here few pre-processing techniques are mentioned, such as **Filtering, Binarization, Cropping, Thinning, Skeletonization, Rotation for Skew Correction, Slant Correction, and Resizing etc.**

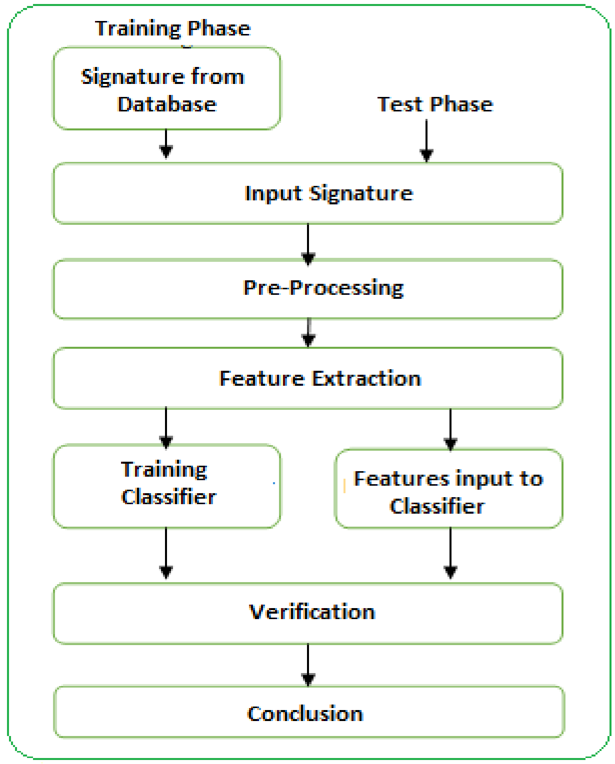

Figure 2. Major Phases in Offline Signature Verification System

1.2.3 Feature Extraction

If the signature verification involves conventional machine learning algorithms, it's necessary to provide handcrafted features to train and test the model. In case signature verification model employs deep learning architecture then the architecture itself takes care of feature engineering. However conventional machine learning methods emphasis on handcrafted feature extraction for classification problem. Once the features are extracted from data forms a feature vector. These feature vectors become knowledgebase which is used to train the model. The trained model further tested against unseen data to examine the accuracy of the model. Features such as **Statistical Features, Global Features, Local Features and Geometric Features** can be extract**.**

1.2.4 Classification

It is a supervised machine learning algorithm, where the data samples are classified based on the label. Classification is a classical machine learning problem where data samples are discriminated based on the features associated with its label. There are many classifiers are available to classify data such as Support Vector Machine, Multi-Layer Perceptron, Naïve Bayes, K-Nearest Neighbour, Decision Tree etc.. If the classification involves two class of data then it is called binary classification. If the classification involves more than two class of data then it is called multi-class classification.

1.2.5 Performance Evaluation

It is necessary to analyse the performance of the designed model. There are several performance metrics are available to check the accuracy of the designed model namely, False Acceptance Ratio, False Rejection Ratio, Equal Error Rate, ROC Curve and Confusion Matrix

1.3 Objectives of the Proposed Research

The objectives of the proposed research work on Offline Signature Verification are to:

- The proposed work is to device efficient algorithms for verification of signature.
- Exploration of global/local descriptor.
- Mathematical morphology based analysis while designing signature verification.
- A combined classifier model shall be developed to provide robustness to signature verification.
- In order to achieve higher accuracy, we explored Support Vector Machine and Multi- Layer Perceptron classifiers are used.

2. Proposed work:

Block wise Binary Pattern: a Robust an Efficient approach for Offline Signature Verification.

2.1 Methodology

The proposed work exploits the variant of local binary patterns called Blockwise Binary Patterns (BBP). In this approach the pre-processed binary image is divided in to 3x3 neighbourhood blocks as shown in the figure 3. Each of the partitioned 3x3 block is labelled as 1 where signature part is present otherwise label as 0. Repeat this labelling for all remaining blocks. A BBP value for central pixel of each block is computed by considering its 8 neighbourhood pixels. This gives binary sequence for each block. Let $P_{i,j}$ be the central pixel for a block. The binary sequence for a block is as follows.

$$B = \{P_{(i-1,\, j-1)},\ P_{(i-1,\, j)},\ P_{(i-1,\, j+1)},\ P_{(i,j-1)}\, ,\ P_{(I,j+1)},\ P_{(i+1,\, j-1)},\ P_{(i+1,j)},\ P_{(i+1,j+1)}\} \qquad (1)$$

Obtain the decimal value for the above binary sequence B. This decimal value represents the binary values of that particular block and which is variant to rotation. To make rotation invariant, perform right shift operation and find decimal equivalent. Which is rotation invariant. Repeat the process for all remaining bits of the binary sequence of the respective block and obtain decimal equivalent value for the same. Finally consider smallest decimal value which is rotational invariant and represents the block. Repeat the entire process for remaining blocks. The obtained BBP values are stored in the form of normalized histogram, which becomes knowledge base to train the signature verification model.

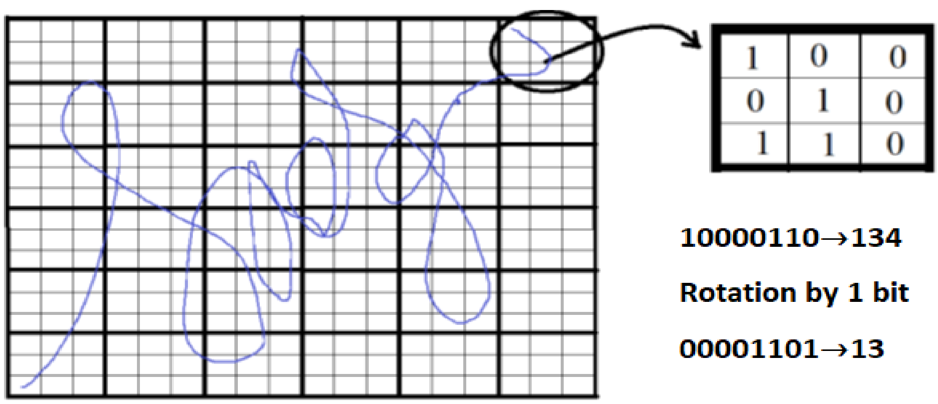

Figure 3. Block wise Binary pattern on a Signature

Steps involved in computing BBP values for an image is as follows

- Divide the signature image in to 3 x 3 neighbourhood blocks.
- In the block if the signature parts is present labelled as 1 otherwise keep it as 0
- Generate the binary sequence in clock wise direction.
- Which is rotational variant, so to make rotational invariant perform right shift operation
- Compute its decimal equivalent.
- Now generate the same binary sequence for all remaining pixels.
- Compute decimal equivalent for all the obtained binary sequence.
- Consider the smallest decimal value, which is rotational invariant and represents the entire block. Which is considered as central pixel value.
- Repeat the entire process for all remaining blocks.

- Obtain the histogram for all central pixel values and normalize the histogram. Which forms the knowledge base to train the model.

2.2 Classification

Classification is the process of discriminating one object image from another. In our proposed approach we employed support vector machine (SVM) for classification. SVM comes under supervised machine learning method (classifier). It can be employed on both classification and regression problems. It's a bilinear classifier can classify two class of object. Here it employees one-versus-one strategy. However SVM can also be exploit on multiclass classification problem due to bilinear in nature it adopts one-versus- rest strategy. Where one class of object will be compared with rest of object. Support Vector Machine (SVM) was introduced in 1992, by Boser, Guyon, and Vapnik in COLT-92. Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data. Support Vector machines can be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory as shown in Figure 4 and Figure 5.

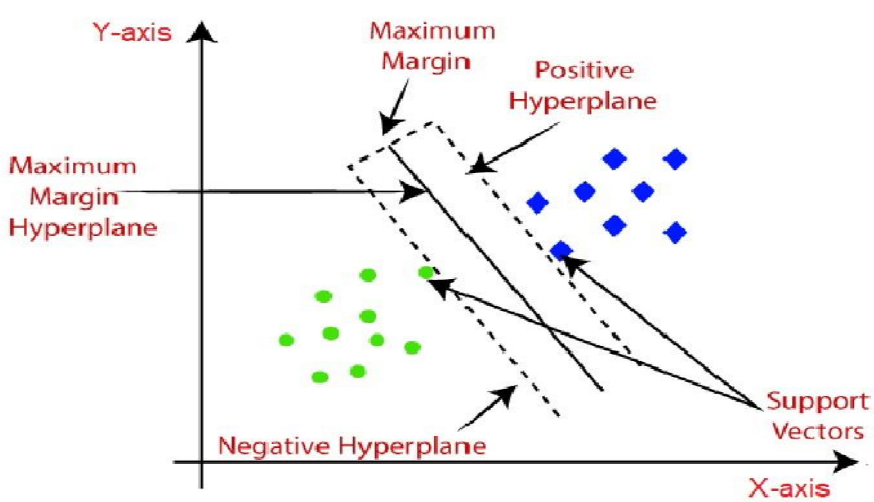

Fig 4. A hyper plane separating two class of objects

This is represented by following formula

S=$\{x| < w, x > +b = 0\}$ --------------------2

Where x be the training set, w is the margin and b be the bias.

The samples above the hyper plane are considered as positive objects label and below are negative objects label.

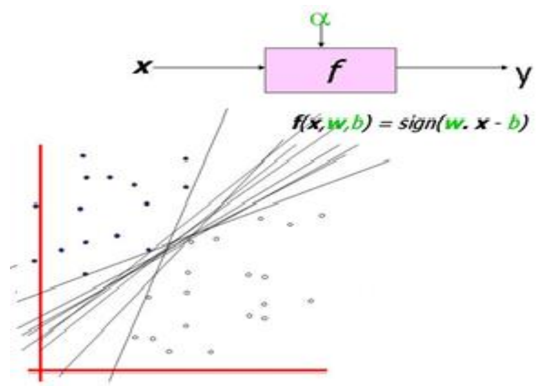

Figure. 5. SVM Hyper plane (Image Curtsey: Andrew W. Moore 2003)

Figure 4 shows there are many fits to classify but still finding best fit is difficult due to less margin.

For input test image, the classification is achieved as fallows

1. The BBP values are computed from the image and its histogram is obtained, par say Bh.

2. Compute the distance between test image and training image using Euclidian distance method.

3. The distance values are arranged in the ascending order of their distance to get top image matches.

2.3 Experimental Results

Experiments are conducted on CEDAR (Center for Document Analysis and Recognition) database, GPDS 160 (Digital Signal Processing Group) which is a subset of GPDS 300 and MUKOS (Mangalore University Kannada Offline Signature) database. CEDAR and GPDS databases are publically available standard databases whereas MUKOS is a regional language Kannada database. The tabular form of experimental set-up and obtained results are as given in Table 1.

Table 1.Details of the Database:

Database	No. of Signers	No. of Genuine signatures	No. of Skilled Forge signatures	Total No of Signatures
CEDAR	55	24	24	2640
GPDS-160	160	24	30	8640
MUCOS	30	30	15	1350

Experimental Set-up for CEDAR dataset:

CEDAR is a well-known publicly available database, stands for Center for Document Analysis and Recognition. Experiments were started with set-1 along with set-3 where 10 genuine and 10 skilled forge signatures are considered for training and for testing around 14 genuine signatures with 14 skilled forgery signatures are considered. Experiments were continued with Set-2 and set-4 with numerical figures such as first 14 genuine signature samples with first 14 skilled forge signature samples were considered for training and tested against remaining both 9 genuine signature samples with 9 skilled forgery signatures. To overcome from the effect of randomness 5 times experiments are repeated for set-2 and set-4 finally average result is considered. The results are tabulated in Table 2, where FAR and FRR are the performance metrics. A comparison study reported in Table 5.

Table 2. Experimental results obtained for CEDAR Database:

Experimental Set-up	Accuracy	FRR	FAR
Set-1	91.55	10.12	6.75
Set-2	93.54	6.06	6.86
Set-3	90.45	10	9.09
Set-4	93.64	8.68	4.04

Experimentation on GPDS-160 dataset

Digital Signal Processing Group (GPDS) of the Universidad de Las Palmas de Gran Canaria, has developed an offline handwritten signature database known as GPDS-300 corpus. We have conducted experiments with set-1 and set-3 test configuration with 10 genuine and 10 skilled forgery samples and tested against remaining 14 genuine and 20 skilled forgery samples. Further in set-2 and set-4 we chooses15 genuine and 15 skilled forgery samples for training and tested against remaining 9 genuine and 15 skilled forgery samples. We computed FAR and FRR as performance measure. The obtained results are reported in Table 3. We have also reported a comparative study in Table 6.

Table 3 Experimental results obtained for GPDS-160 Database

Experimental Set-up	Accuracy	FRR	FAR
Set-1	97.39	5.06	8.2
Set-2	97.25	0.58	4.9
Set-3	96.08	0.8	6.95
Set-4	97.1	0	5.80

Experiments on MUKOS Dataset

MUKOS (Mangalore University Kannada Offline Signature) database is a regional language Kannada dataset. All experiments are conducted in terms of set-1, set-2, set-3 and set-4. In set-1 and set-2 there are 10 genuine and 10 skilled forgeries are chosen for training and 15 genuine signature and 5 skilled forgeries are chosen for testing. Experiments on set-2 as well as on set-4 we considered 15 genuine signatures and 15 skilled forgeries for training and 15 genuine signatures and 15 skilled forgeries are tested against. Repeat the set-2 and also set-4 experiments 5 times to overcome from the effect of randomness and considering the average result. The metrics FAR and FRR used to measure the accuracy of the approach. Results obtained for MUKOS dataset is tabulated below (Tables 4) and a comparison analysis is reported in Table 7.

Table 4 Experimental results obtained for MUKOS Database

Experimental Set-up	Accuracy	FAR	FRR
Set-1	97.39	8.2	5.06
Set-2	97.25	4.9	0.58

Set-3	96.08	6.95	0.8
Set-4	97.1	5.80	0

Table 5. Experimental Results obtained for CEDAR Dataset - A comparison

Proposed by	Classifier	Accuracy	FAR	FRR
Kalera et al., (Kalera et al., 2004)	PDF	78.50	19.50	22.45
Chen and Shrihari (Chen and Srihari, 2005)	DTW	83.60	16.30	16.60
Kumar et al., (Kumar et al., 2010b)	SVM	88.41	11.59	11.59
Pattern Spectrum (Shekar et al., 2013)	EMD	91.06	10.63	9.4
Surroundedness (Kumar et al., 2012)	MLP	91.67	8.33	8.33
Inter Point Envelop (Kumar et al. 2014)	SVM	92.73	6.36	8.18
Proposed Approach	**SVM**	**93.64**	**8.68**	**4.04**

Table 6 Experimental result obtained for GPDS-300/160 dataset: A comparison

Model Proposed	Classifier type	Accuracy	FAR	FRR
Ferrar et al., (Ferrer et al., 2005)	SVM	86.65	13.12	15.41
	HMM	–	12.60	14.10
Vargas et at., (Vargas et al., 2011)	SVM +LBP	87.28	6.17	22.49
Solar et al., (Ruiz-Del-Solar et al., 2008)	Bayseian	84.70	14.20	16.40
Surroundedness (Kumar et al., 2012)	MLP	86.24	13.76	13.76

Pattern Spectrum (Shekar et al., 2013)	EMD	91.06	10.63	9.4
Proposed Approach	**SVM**	**97.27**	**3.167**	**2.014**

Table 7 Experimental outcome on MUKOS database- A Comparison

Method	Classifier	Accuracy	FAR	FRR
Shape based Eighen Signature [9]	Euclidian Distance	93.00	11.07	6.40
Pattern Spectrum [4]	EMD	97.39	5.6	8.2
Proposed Approach	**SVM**	**97.39**	**8.2**	**5.06**

3. A Novel Feature Extraction Technique: Multi-Scale Local Binary Patterns

3.1 Methodology

We have also proposed feature extraction technique namely Multi-Scale Local Binary Patterns. This approach represents a powerful feature representation method called Multi-scale Local Binary Patterns for offline signature verification. The multi-scale representation oriented local binary patterns can be obtained by changing the radius R value of Local Binary Patterns (LBP) operator and combining the LBP features at different scales. In this proposed approach the LBP operator is applied at 3 different scales by varying the radius R value and at each scale equal number of pixels are considered for the processing. Finally, by cascading a group of LBP operators at 3 different scales over a signature image with fixed number of pixels at each scale and combining their results, a multi-scale representation LBP can be obtained. This essentially represents nonlocal information. Features fusion is performed by the linear combination of the histogram corresponding to 3 different radii results in a multi resolution (scale) feature vector. Support Vector Machine (SVM) is a well-known classifier employed to classify the signature samples. Experimental results on standard datasets like CEDAR and a regional language datasets shows the proposed technique's performance. A comparative analysis with few well known methods is also presented to demonstrate the performance of proposed technique.

In this work, we propose a Multi-scale Local Binary Patterns (MSLBP) to extract the local as well as global features from the signature image. The LBP features are extracted from signature image at different radii and are stored in the form of histograms. The fusion of histogram features at various scales are performed to form a single feature vector. The LBP is a gray-scale texture descriptor which describes the local spatial structure of the texture of an image. Based on central pixel value in an image, a code sequence is generated by keeping it as a threshold with its neighbourhood pixel values.

$$\text{LBP}_{\text{P, R}} = \sum_{P=0}^{P-1}(gp - gc)2^{p} \text{ ---------------------------3}$$

$$S(x) = \begin{Bmatrix} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{Bmatrix}$$

Here g_c represents the central pixel gray value, g_p neighbourhood value, P represents the number of neighbourhood pixels involved and $\boldsymbol{R}$ represents the radius of the neighbourhood pixels. The LBP values are computed for each pixel $\boldsymbol{P}_{i,j}$ by considering N neighbouring pixels. The N neighbouring pixels of P are considered in clockwise direction resulting a binary stream S. In case of $N = 8$ with $\boldsymbol{R} = 1$, the binary stream is defined as follow

$$S = \{P_{(i-1, j-1)}, P_{(i-1, j)}, P_{(i-1, j+1)}, P_{(i,j-1)}, P_{(I,j+1)}, P_{(i+1, j-1)}, P_{(i+1,j)}, P_{(i+1,j+1)}\} \text{------------4}$$

Compute the decimal equivalent d_i of the binary sequence S. The resulting value d_i is variant to rotation. To make it invariant to rotation shift S one bit towards right side by applying right shift operator. This will results in another decimal equivalent d_j of S. Repeat the process for all the remaining bits in binary sequence S to obtain N decimal equivalent values.

$$D = d_1, d_2, \ldots, d_N \text{ -------------------------------5}$$

The minimum decimal value in the set D is chosen as the value for pixel Pi, j. The value of radius R can be varied. If R = 1 then the neighbouring 8 pixels at distance 1 are taken as the binary stream representing the pixel under consideration. The radius can be extended to 2, 3, etc. The neighbouring pixels for a given pixel at R = 1,2 and 3 are shown in the Figure 6.

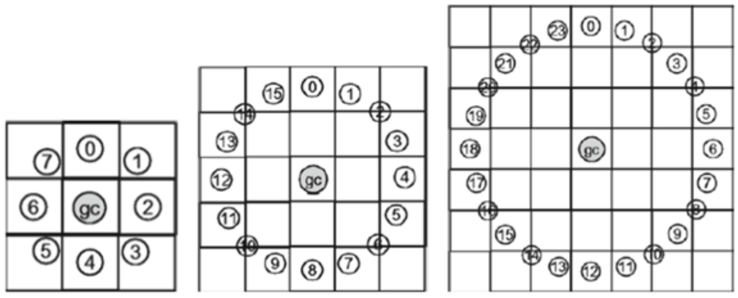

Figure.6 (a) LBP with R = 1 and P = 8 (b) LBP with R = 2 and P = 16 (c) LBP with R = 3 and P = 24

In the proposed approach we have used 3 scales, (R = 1, P = 8), (R = 2, P = 8), (R = 3, P = 8). The input image is applied with LBP(R = 1 and P = 8) operator. The LBP transformed image is converted into a histogram H_1 and stored in a knowledge base. The process is repeated with LBP(R = 2, P = 8) and LBP(R = 3 and P = 8) giving rise to two LBP transformed images which are converted to histogram H_2 and H_3 correspondingly and are stored in knowledge base. The Histograms are combined to form a single histogram representing the resultant MSLBP feature vector for input signature image.

The Figure 6 shows the input signature image and the transformed images after applying the LBP operators LBP(R = 1, P = 8), LBP(R = 2, P = 8), LBP(R = 3, P = 8), LBP(R = 4, P = 8) and LBP(R = 5, P = 8) respectively. The classification is done using SVM as follows.

3.2. Classification

In this work we have used the well-known classifier Support Vector Machine (SVM) to classify signatures samples. The Support Vector Machine is intend to develop a model which learns from training samples based on the extracted features to predict target values of test samples. The dataset is divided into training set as well as test set during the classification process. Every sample in the training set having its own target value called class label with set of features known as observed variables. Support vector machines are a bunch of supervised classification and regression algorithms. They are bi-linear by nature and used to classify two class objects. The Multi-SVM can be used to classify more than two class objects, in this case Multi-SVM uses one versus all strategy. The aim of SVM is to separate objects of different class by maximizing.

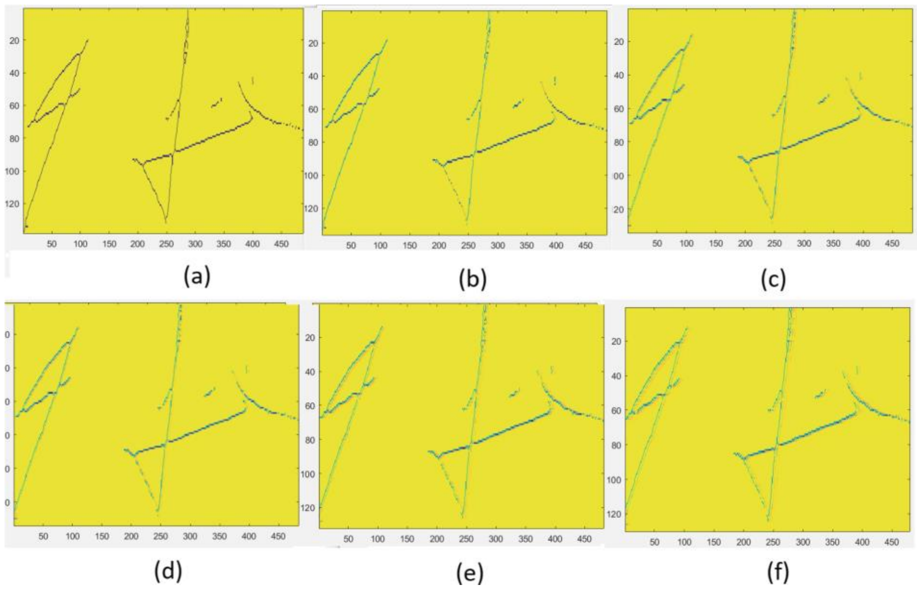

Fig. 7. (a) Original image; (b) LBP with r = 1 and n = 8; (c) LBP with r = 2, n =8; (d) LBP with r = 3, n = 8; (e) LBP with r = 4, n = 8; (f) LBP with r = 5, n = 8.

The margin of a hyper plane. The vectors which define the hyper plane are the support vectors.

$$m = 2 / (||w||) \qquad (6)$$

Where m is the margin and w is the width of the hyper plane.

$$w^T X + b = 1 \qquad (7)$$

Equation 7 represents the upper boundary of the hyper plane.

$$w^T X + b = 0 \qquad (8)$$

Equation 8 represents the center of the hyper plane.

$$w^T X + b = -1 \qquad (9)$$

Equation 7 represents the lower boundary of the hyper plane.

For classification of N classes, N SVM classifiers are required. Therefore, in the proposed work we employed each SVM classifier for each writer. Here the SVM classifier uses one versus all strategy for classification of signatures. The next section presents the experimental results in detail.

3.3 Experimentation Results and Discussion

The experiments are conducted on publicly available well-known dataset namely CEDAR (Center for Document Analysis and Recognition) database. Further we continued the experiments also on Local Regional Kannada dataset namely MUKOS (Mangalore University Kannada Offline Signature) corpus. Dataset details are reported in Table 8.

The features database contains MSLBP histograms, obtained from both datasets. The MSLBP features are extracted from genuine as well as skilled forgery signatures. The signature samples are categorized into training set and test set from both the dataset. Experiments are carried out in 4 epochs. In epoch-1, we chosen first 10 signatures of both genuine as well as skilled forgeries to train the model and remaining samples are used to test.

Table 8. Datasets details

Datasets	Number of Signature Contributors	Number of genuine signatures	Number of skilled forgeries	Total number of signatures
CEDAR	55	24	24	2640
MUKOS	30	30	15	350

In set-2, we considered the first 15 genuine samples along with first 15 skilled forgeries to train and remaining samples are used to test. For set-3, 10 genuine along with 10 skilled forgeries are chosen randomly for training and for testing remaining samples are used. Lastly for set-4, again randomly chosen 15 genuine signatures and 15 skilled signatures are considered to train and remaining samples used to test the proposed model. To avoid the impact of randomness, experiments are repeated for set-3 as well as set-4 and finally we considered average results and are tabulated.

Experiments on CEDAR Dataset:

CEDAR is a well-known publicly available database, stands for Center for Document Analysis and Recognition. Experiments were started with set-1 along with set-3 where 10 genuine and 10 skilled forge signatures are considered for training and for testing around 14 genuine signatures with 14 skilled forgery signatures are considered. Experiments were continued with Set-2 and set-4 with numerical figures such as first 14 genuine signature samples with first 14 skilled forge signature samples were considered for training and tested against remaining both 9 genuine signature samples with 9 skilled forgery signatures. To overcome from the effect of randomness 5 times experiments are repeated for set-2 and set-4 finally average result is considered. The results are tabulated in Table 9, where FAR and FRR are the performance metrics.

Table 9. Obtained Experimental Results on CEDAR Dataset:

Experimental set-up	Accuracy	FRR	FAR
Set-1	94.74	4.0	5.6
Set-2	92.72	9.29	5.25
Set-3	90.58	11.94	6,88
Set-4	91.05	10.60	9.2

From the literature, we found the experimental results of few well known approaches on CEDAR dataset. We made a compararision analysis presented in Table 10 shows the improvements in accuracy by the proposed approach.

Table 10. Experimentation results on CEDAR dataset: A Comparison

Proposed by	Classifier	Accuracy	FAR	FRR
Kalera et al. [22]	PDF	78.50	19.50	22.45
Chen and Shrihari [23]	DTW	83.60	16.30	16.60
Kumar et al. [24]	SVM	88.41	11.59	11.59

Pattern Spectrum [4]	EMD	91.06	10.63	9.4
Surroundedness [1]	MLP	91.67	8.33	8.33
Inter point envelop [9]	SVM	92.74	4.0	5.6

Experiments on MUKOS Dataset

MUKOS (Mangalore University Kannada Offline Signature) database is a regional language Kannada dataset. All experiments are conducted in terms of set-1, set-2, set-3 and set-4. In set-1 and set-2 there are 10 genuine and 10 skilled forgeries are chosen for training and 15 genuine signature and 5 skilled forgeries are chosen for testing. Experiments on set-2 as well as on set-4 we considered 15 genuine signatures and 15 skilled forgeries for training and 15 genuine signatures and 15 skilled forgeries are tested against. Repeat the set-2 and also set-4 experiments 5 times to overcome from the effect of randomness and considering the average result. The metrics FAR and FRR used to measure the accuracy of the approach. Results obtained for MUKOS dataset is tabulated in Table 11 and comparison study is reported in Table 12.

Table 11 Experimentation on MUKOS database:

Experimental Set-up	Accuracy	FRR	FAR
Set-1	97.73	0.53	4
Set-2	97.25	0.58	4.8
Set-3	97	1.2	4.6
Set-4	98.6	0.8	2.0

Table 12 Experimental outcome on MUKOS database- A Comparison

Method	Classifier	Accuracy	FAR	FRR
Shape based Eighen Signature [5]	Euclidian Distance	93.00	11.07	6.40
Pattern Spectrum [4]	EMD	97.39	5.6	8.2

Proposed Approach	**SVM**	**98.6**	**0.8**	**2.0**

A comparative study carried out on several proposed approach from different authors on MUKOS dataset and is reported in Table 12.

Conclusion:

In this work we have briefly explained the two proposed approach. These two approaches are comes under texture descriptors and the final conclusion is as follows.

The proposed method efficiently classifies genuine signature from forge. The obtained results showcases the efficiency of the method. In this work, we have designed an efficient and robust approach namely Block wise binary pattern for offline signature verification. The input image is pre-processed and the dominant features are obtained using BBP method. The features are represented using normalized histogram.

The classification is done using SVM classifier. Extensive experimentation is conducted on well-known publicly available signature dataset: CEDAR, GPDS- 160 (a sub-corpus of GPDS-300) and a regional language signature dataset called MUKOS. In order to highlight the superiority of the proposed approach, a comparative analysis is provided with the state-of-the-art off-line signature methods on CEDAR and GPDS-160 dataset. It is found that the proposed approach is simple to implement, computationally efficient and accurate in terms of classification.

In the second work we tried to explore Multi-scale Local Binary Patterns for offline signature verification. The Local Binary Patterns is a well-known powerful texture descriptor which captures local features. But when we extract local features, which are normally represents minute area of an image this leads to limitation of representing broader or larger area. To overcome from this limitation we made an attempt to exploit Multi-scale Local Binary Pattern for offline signature verification. This helps to capture features at different radius of the image by varying its radii. From the MSLBP we can effectively represent both local information (micro structure) as well as global information of an image.

We conducted extensive experiments on CEDAR database, which is a publicly available well known database. We also conducted experiments on MUKOS data corpus, which is a regional Kannada language offline signature database. Further we made a comparative analysis wherein we found that, the proposed approach performs better than some of the well-known approaches on the CEDAR dataset. It is observed experimentally that, the implementation of MSLBP is simple yet gives high accuracy in signature verification task.

4. Proposed Approach:

Offline Signature Verification Based on Partial Sum of Second-Order Taylor Series Expansion

The proposed method uses partial sum of first finite number of terms of second-order Taylor series expansion technique for offline signature verification. This process involves three important stages: pre-processing, feature extraction, and classification. During pre-processing stage, the Otsu's binarization method is applied on signature samples. This binarization process adds some noise which was later removed by con- ducting morphological filter operations. Later, the thicknesses of strokes of signatures are normalized by performing morphological operations like thinning and dilating. The following section presents the process of feature extraction and classification.

4.1 Taylor Series Expansion

Let function f(x) be the function that is continuously infinitely differentiable in a neighbourhood. The Taylor series expansion for f(x) on a point x=a indicates the function in a small neighbourhood of a point a. An expression for infinite Taylor series expansion for a function f(x) at x=a is

$$f(x) = \sum_{n=0}^{\infty} \frac{f^n(a)}{n!} (x-a)^n \qquad (1)$$

Here n! Is factorial of n,

a is real or complex number,

f^n (a) n^{th} derivative of f evaluated at the point a.

When the functional value and the values of its derivatives are known at x=a, then the function can be estimated at all the points of the neighbourhood of a. then above expression can be written as

$$f(x) = \sum_{n=0}^{N} \frac{f^n(a)}{n!} (x-a)^n + R_n \qquad (2)$$

Here Rn represents Taylor's remainder. Assuming Rn tends to zero as $n \to \infty$ for a small neighbourhood, then the partial sum of TSE is calculated for N finite number of terms yields approximation of function f(x). The advantages of TSE are explored here to extract the signature features in a local region.

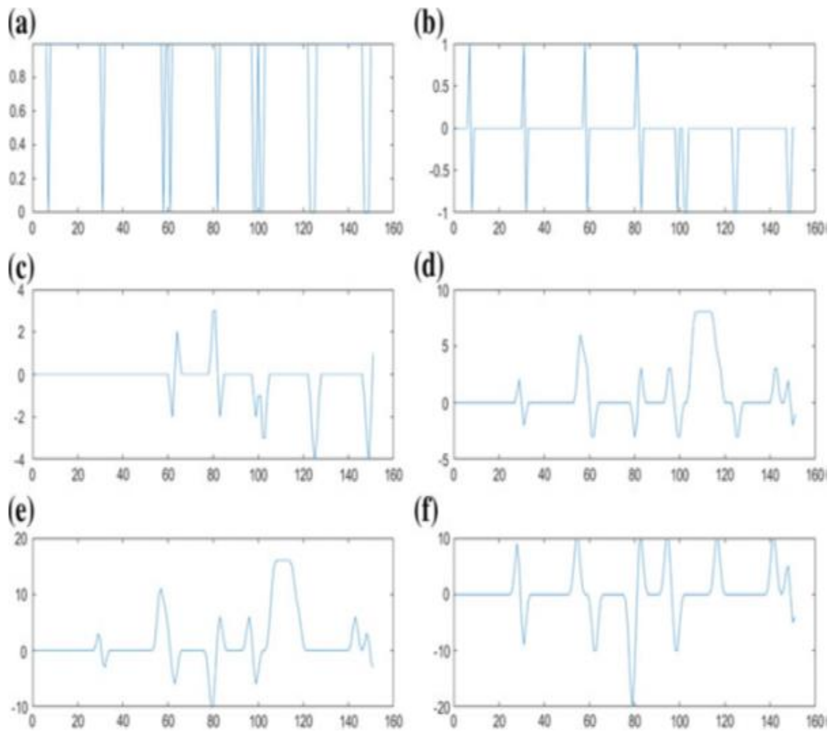

Figure.8 a) 1D signal of the signature from CEDAR database. b) to f) order of first-fifth derivatives of the signal. The Y-axis shows the range from which variation in derivatives. The range increases as against increase in order.

These are based on the first and second order derivatives obtained separately at eight different scales and then encoded on the basis of zero-crossings of the convolution outputs. First derivatives reveals the minute local features, and the second derivatives reveals features of concavity and convexity of the edges. It is a well-known fact that the higher order derivatives can well extract the global information within a neighborhood; hence, we have taken third- order derivatives also. Figure 8 shows the output derivatives of a 1D signal obtained for a signature sample of CEDAR database. The range of values over the vertical axis tells the range of variations in derivatives; this becomes wider for higher orders. It is verified empirically that derivatives above fifth order fail to contribute much. It is shown in Figure.8 that there is small variation among fourth and fifth derivatives.

In order to calculate horizontal as well as vertical higher order derivatives, we have extended Sobel's kernel which uses coefficients of *n*th-order binomial expansion, i.e., the elements of the *n*th-order kernel are also elements of the *n*th row of Pascal triangle and are obtained by the coefficients of the binomial expansion $(a + b)^n$, a and b becomes unity. For example, the kernels to calculate third-order derivatives along horizontal direction and vertical direction are given below.

$$\begin{bmatrix} -1 & -3 & -3 & -1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 3 & 3 & 1 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & 0 & 1 \\ -3 & 0 & 0 & 3 \\ -3 & 0 & 0 & 3 \\ -1 & 0 & 0 & 1 \end{bmatrix}$$

The summation of horizontal and vertical partial sum of TSE forms the features for that point x=a. Histogram of 10 bins is used to represent the features.

4.2 Classification based on Support Vector Machine

We employed Support Vector Machine (SVM) for Classification purpose. SVM works on the basis of decision planes that defines decision boundaries. A decision boundary is one that separates a set of objects which belongs to different classes. SVM is to classify the samples by training the model. Once the model is trained, which essentially estimates the values of test data.

Let n be a training set $\{(x_i ; y)\}_{i=1}^{n}$ where $x_i \epsilon R^L$ is chosen from X domain and label y_i is an integer of Y= {0, 1}. Finally, the aim of SVM classifier is to build a model that essentially discriminates unseen data depends on the matching score of feature vector of both training sample and test sample. It is the process of learning a function f: $X \rightarrow Y$ which derives an instance y of Y. for a given instance of pair of labels (x_i, y_i), i=1,..., l where $x_i \epsilon R^n$ and $y \epsilon \{0,1\}^l$, for the following optimization problem, the SVM classifier requires the solution:

$$\min_{(w, b, \varepsilon)} \frac{1}{2} W^T W + C \sum_{i=1}^{l} \varepsilon_i \qquad (3)$$

Subjected to

$$y_i (w^T \phi (x_i) + b) \geq 1 - \varepsilon_i \qquad (4)$$

and

$$\varepsilon_i \geq 0 \tag{5}$$

Let the training vectors x_i are drawn into a hyper plane space by the function ϕ**.** the SVM draws a linear separating hyper plane which tends to widen the maximum margin. $C > 0$ is the penalty parameter of the error term, and kernel trick is used transform objects from lower dimensional space to higher dimensional space. Since SVM is a bilinear classifier, N SVM classifiers require to classify N classes. So, inthis proposed method, we used one against all strategy which employs N number of SVM classifiers for N number of writers.

4.3 Experimentation Results and Discussions

Here, we brought down experimental results carried out on the signature databases, namely, The Centre of Excellence for Document Analysis and Recognition (CEDAR) and Mangalore University Kannada Off-line Signature corpus (MUKOS) a regional language offline signature corpus. Both the databases contain different number of signers with various genuine and forge signatures. The experimental setup of both datasets is presented in Table 13.

The knowledge repository contains the TSE features extracted from every sig- nature sample of the dataset. It includes both genuine signatures and skilled forge signatures. From datasets, signatures are considered into two sets: one is training set and second is testing set. The samples are varied in number. Experiments are conducted in four sets. For set-1, we considered first ten genuine signatures and first ten skilled forges signatures for training and are tested against the remaining signatures of same dataset. Set-2 considers first 15 genuine signatures along with first 15 skilled forge signatures for training and other samples of same dataset are tested. For set-3, we considered ten genuine signatures and ten forge signatures which are randomlyselected to train and other signatures are to test. Set-4 considers 15 randomly chosen samples from the same datasets for training and other samples for testing. Experiments are repeated for 5 times for set-3 and set-4 to avoid randomness, and results are tabulated.

Table 13. Datasets details

Datasets	Number of Signature Contributors	Number of genuine signatures	Number of skilled forgeries	Total number of signatures
CEDAR	55	24	24	2640
MUKOS	30	30	15	350

Experiments on CEDAR Dataset:
CEDAR is a well-known publicly available database, stands for Centre for Document Analysis and Recognition. Experiments were started with set-1 along with set-3 where 10 genuine and 10 skilled forge signatures are considered for training and for testing around 14 genuine signatures with 14 skilled forgery signatures are considered. Experiments were continued with Set-2 and set-4 with numerical figures such as first 14 genuine signature samples with first 14 skilled forge signature samples were considered for training and tested against remaining both 9 genuine signature samples with 9 skilled forgery signatures. To overcome from the effect of randomness 5 times experiments are repeated for set-2 and set-4 finally average result is considered. The results are tabulated in Table 14, where FAR and FRR are the performance metrics. We have made a comparative study and the results are shown in Table 15.

Table 14. Obtained Experimental Results on CEDAR Dataset

Experimental set-up	Accuracy	FRR	FAR
Set-1	94.28	5.97	5.45
Set-2	94.09	7.27	4.54
Set-3	95.25	5.6	3.83
Set-4	93.63	10.3	2.42

Table 15. Experimentation results obtained for CEDAR dataset – A comparison

Proposed by	Classifier	Accuracy	FAR	FRR
Kalera et al.[22]	PDF	78.50	19.50	22.45

Chen and Shrihari [23]	DTW	83.60	16.30	16.60
Kumar et al. [24]	SVM	88.41	11.59	11.59
Pattern spectrum [4]	EMD	91.06	10.63	9.4
Surroundedness [1]	MLP	91.67	8.33	8.33
Inter-point envelope [9]	SVM	92.73	6.36	8.18
Proposed approach	SVM	95.25	5.6	3.83

Experiments on MUKOS Dataset:

We also conducted experiments on regional language dataset, namely, Mangalore University Kannada Off-line Signature [MUKOS] that is a Kannada regional language corpus. The experiments are continued with set-1 and set-3. This setup consists of ten genuine and ten skilled forgery signatures, and from this feature vector was obtained. This forms the training model. Testing model is constructed with 15 genuine and 5 skilled forgery signatures. Similarly, experiments are also conducted to train from set- 2 and set-4; here, 15 genuine and 15 skilled forge signatures are considered to obtain the feature vector. Then, 15 genuine and 15 skilled forge signatures are considered to test. The accuracy of the proposed approach obtained from set-1 to set-4 is tabulated in Table 16. The experimentation for set-2 and set-4 is the average of five instances of experimentations with randomly chosen samples. A comparative observation onthe MUKOS dataset with some of the past works is tabulated in Table 17.

Table 16. Experimental results obtained for MUKOS dataset

Experimental set-up	Accuracy	FRR	FAR
Set-1	96.8	0.8	5.6

Set-2	96.8	2.8	3.6
Set-3	98.26	1.3	2.13
Set-4	98.93	0.5	1.6

Table 17. Experimental results for MUKOS dataset- a comparative analysis

Method	Classifier	Accuracy	FAR	FRR
Shape-based eigen signature [9]	Euclidean distance	93.00	11.07	6.40
Pattern spectrum [4]	EMD	97.39	5.6	8.2
Proposed approach	SVM	98.93	0.5	1.6

4.4 Conclusion

This work presents a novel signature verification technique which uses partial sum of second-order Taylor series expansion (TSE) for offline signature verification. Finite sum of TSE computed on an arbitrary small neighborhood can approximate the function extremely well. This is a strong and feasible mechanism to extract the local features of signature. We present kernel structures by incorporating the Sobel operators to compute the higher order derivatives of TSE. The experimental results obtained on offline signature datasets, namely, CEDAR and MUKOS, demonstrate the improvements in the classification accuracy compared to some of the well-known offline signature verification methods.

5. Proposed Approach:

Spatial Pyramid Image Representation with DCT Features for Offline Signature Verification

5.1 Methodology

The proposed methodology uses the spatial pyramid image technique on the two dimensional signature images. The global and local DCT features are extracted from the signature image and the standard deviation and count of non-zero DCT coefficients corresponding to each AC frequency are computed forming the feature vector. We have made use of the fact that authentic signatures appear accurate and fluent the lack of which in the signature implies forgery. Standard deviation of DCT coefficients is a good measure of representing the spread of intensities in an image. The spatial pyramid is an extension of the bag of features that consists of collection of the order-less features. The Figure 9. illustrates the spatial pyramid applied on a signature image.

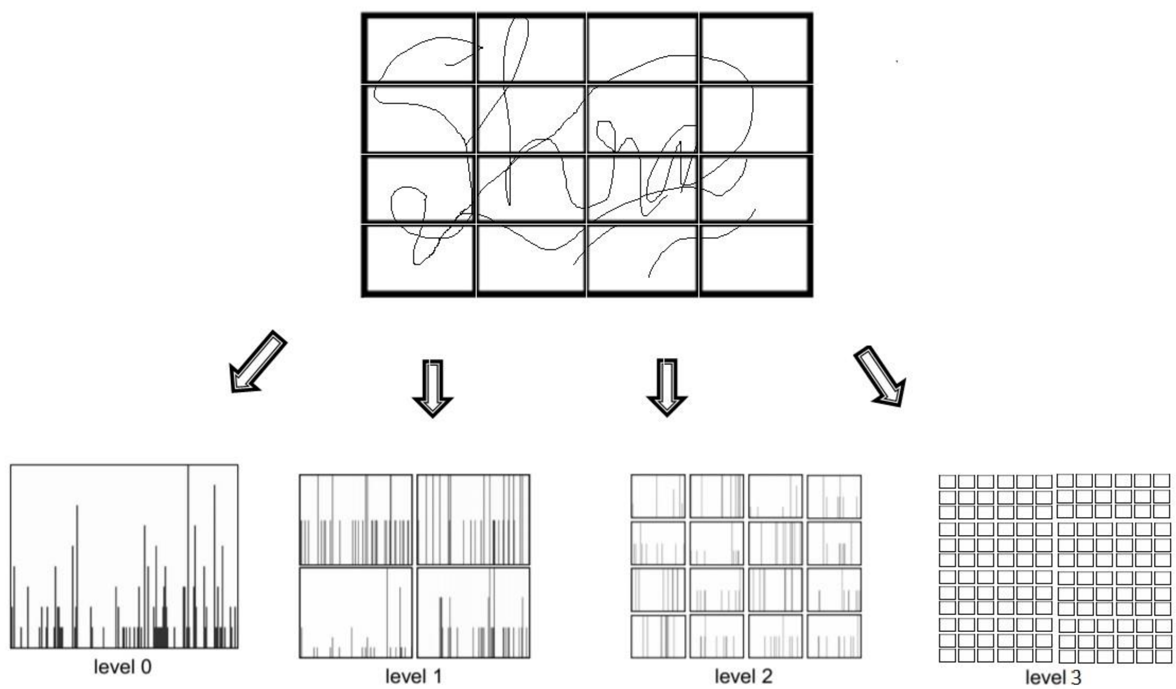

Figure 9. Spatial pyramid with 4 levels. Level 0: Signature image, level 1: Image is partitioned into 4 blocks. Level 2: Image is partitioned into 16 sub-blocks, Level 3: Image is partitioned into 8x8 non-overlapping sub-blocks.

5.2 Classification:

Support Vector Machines (SVM) is employed to perform classification. SVM learns a linear decision boundary for a given training set. It finds a decision plane that maximizes the margin. "Given a set of n training samples”.

5.3 Experimental Results and Discussions:

Here, we brought down experimental results carried out on the signature databases, namely, The Centre of Excellence for Document Analysis and Recognition (CEDAR) and Mangalore University Kannada Off-line Signature corpus (MUKOS) a regional language offline signature corpus. Both the databases contain different number of signers with various genuine and forge signatures. The experimental setup of both datasets is presented in Table

Experimental Results on CEDAR dataset:

We have carried out 4 sets of experiments on CEDAR dataset. The results are presented in the Table 18 and the comparative study reported in the Table 19

Table 18. Experimental Results for CEDAR dataset

Experimental Set-up	Accuracy	FRR	FAR
Set-1	92.12	7.8	7.9
Set-2	94.65	5.28	4.91
Set-3	92.82	6.8	7.4
Set-4	94.88	5.37	5.21

Table 19 Experimental Results for CEDAR Dataset - A comparison:

Proposed by	Classifier	Accuracy	FAR	FRR
Morphological Spectrum [4]	Earth Mover Distance	91.06	10.63	9.4
Inter Point Envelop [9]	SVM	92.73	6.36	8.18
Proposed Approach	SVM	94.88	5.37	5.21

Experimental Results on MUKOS dataset:

We also conducted experiments on regional language dataset, namely, Mangalore University Kannada Off-line Signature [MUKOS] that is a Kannada regional language corpus.

Table 20. Experimental Results for MUKOS dataset

Experimental Set-up	Accuracy	FRR	FAR
Set-1	99.2	0.0	1.6

Set-2	98.26	1.0	2.4
Set-3	96.2	2.8	4.8
Set-4	96.4	2.0	5.4

Table 21. Experimental Results for MUKOS dataset: A Comparison

Proposed by	Classifier	Accuracy	FAR	FRR
Shape based Eighen Signature [9]	Euclidian Distance	93.00	11.07	6.40
Pattern Spectrum [4]	EMD	97.39	5.6	8.2
Proposed Approach	SVM	99.2	0.0	1.6

5.4 Conclusion

In this work, we have used Spatial Pyramid image representation based technique with global and local features captured through DCT coefficient at various levels for offline signature verification. The spatial pyramid feature vector is an extension of an order less bag-of-features. We employed spatial pyramid with 4 levels and taken the entre signature image at the first level. The rest of the 3 levels in the pyramid consists of images with 4 partitions, 16 partitions and 8x8 non overlapping blocks. Our approach captures both local and global DCT features from the image and its subblocks at various levels. The AC DCT coefficients obtained are represented in the form of matrix. The variation in the statistical properties of AC coefficients of the image is made use of in detecting the forgery. For that, the standard deviation and count of non-zero DCT coefficients corresponding to each row in the DCT matrix is found out. Standard deviation of DCT coefficients is a good measure of representing the spread of values in an image. The extracted feature vector consists of the standard deviation and the number of non-zero values in DCT matrix. The Support Vector Machine (SVM) is used for the classification. The Experimental results reveals the performance of the proposed approach.

6. Publications

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To be communicated:

1. Spatial Pyramid Image Representation with DCT Features for Offline Signature Verification

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