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Handwritten Signature Verification Based on Surf Features Using Hmm

Ms. Rajpal Kaur[1], Ms. Pooja Choudhary[2]
India

ABSTRACT
Handwritten signature broadly used biometric which include elevated intrapersonal variance .Signature are generally used as the personal identification apparatus for human that the necessitate for verification system. Two types verification is performed generally online (dynamic) and offline signature verification (static). The static is offline technology that is used for documents authentication, the dynamic is online technology for signal processing and pattern recognition. The main motive of handwritten signature verification is to reduce fraud in financial transactions, security in crossing the international borders and boarding an aircraft. In this paper present the signature verification on Punjabi database of 50 persons. The features are extracted using the Gabor filter and matching is performed using SURF features and critical point matching. The classification is based on HMM classifier and the experimental results shows the verification accuracy rate of 97%.
General terms: Biometrics, Signature verification, signature matching.
Keywords:- handwritten Signature verification, preprocessing, feature extracted, Classifiers

I. INTRODUCTION

Biometric identification methods such as signature verification, signature recognition, fingerprints, iris scanning, signature and DNA analysis are increasing because of its unique features. Biometrics verification is used to recognize people based on their extracted physical or behavioral features. These features have some properties such as uniqueness,

Acceptability, scalability, collectability, portability and the cost to implement biometric system. The Behavior features include the measure the action of person such as speaking, writing and motion of body. These are static because it changes over time due to age effect and over enhancement and development factors. The physical features are the type of biometric that includes fingerprints, palm print, retina, finger geometry and DNA. The signature verification is of two types online signature verification that works on signal processing and pattern recognition so it is also called static signature verification and other is offline signature verification that works on handwritten documents so it's known as Dynamic signature verification. In online signature verification the data acquisition done by touch screen, stylus and touch screen. These instruments generate the dynamic value

Location, pen pressure, co-ordinate values, speed of signature or time etc. online signature verification includes dynamic properties like duration, flow of pen tip, velocity, pressure point and acceleration. In the offline signature verification data acquisition done by scanning the image. The offline signature verification is more challenging than the online signature because the features are extracted from the static 2-D image of signature. The main difficulties in offline signature is highly stylish signatures and unconventional writing, on- repetitive nature of verification of signatures, because of age,illness,stress level, geographic locations and perhaps to some extent the emotional state of the person. The offline signatures having a lot of noise included and information obtains slightly. The need of signature authentication is to differentiate between original signatures and forger. There are three different types of forgeries:

i. **Hit-or-Miss Forgery: -** This is straightforward type of forgery that can be uncovered effort eddy. In this forger create a signature in its own style or having lacking any knowledge of original signatures.
ii. **Well-versed forgery: -** Forger may be expert in copy original signature. In other words forger has knowledge about original signatures, how's it look like.
iii. **Amateur Forgery: -** In this forger keep an eye on original signature and tries to create sign forger is not experienced reason.

II. PREVIOUS WORK ON FEATURES

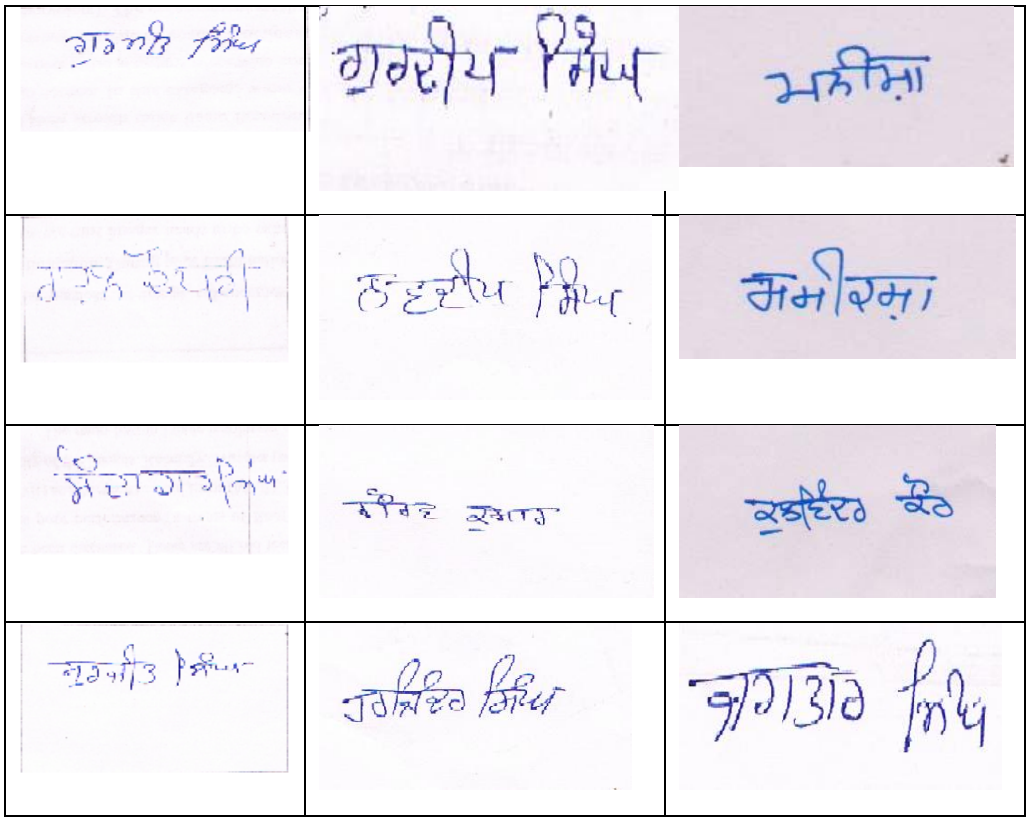
In the offline signature verification the most challenging problem is automated signature verification is to extract feature which is robust against this normal variability and at the same time

discriminate between actual and forged samples. A novel method is for extracting easily scale invariants and computed rotation feature for offline signature verification [1]. The most useful technique support vector machine is a statistically sound technique which is used for ability of learning well separating hyper planes in elevated dimensional feature space. One of the aims of this technique is optimizing the generalization bounds [2]. This paper present the idea following the extraction for stroke speed is to extract dynamic feature from a static signature. In order to attain the speed of stroke, the intensity of the stroke is considered [3].the paper cover all the important part used in the field by processing on feature extraction, to exhibit the fusion of features, names, diagonals and statistical features are extracted from 25 equal zones are used as input pattern to test the performance of the model [5]. A signature by an approved persons is considered to be the "seal of approvals" is remain the mainly prefers mean of authentication on the method in consist of image processing, geometric, features extraction, neural network training with extraction features and verification [6].In this paper the performance of an offline signature verification system concerning hindi signatures, whose style is different from western scripts, has been explore. The gradient and Zernike and Support vector machine were considered for verification [7]. In this paper the proposed model has two stages: preprocessing and Eigen signature construction. Convert the scan signatures to a shape form and Eigen signature construction is proposed for extracting the feature vector from a shape formed signature [8].

III. SIGNATURE DATABASE

For training and testing of the signature verification system 200 signatures are used. The signatures are taken from 50 persons. The template is shown in fig. 1. Each of these persons signed two original signatures and two forger signatures. In the training set the total number

Of signatures 200 are used. In order to make the system robust, signer were asked to use as much as variation in their signature size and shape and the signature are collected different times without seeing the signature they signed before.



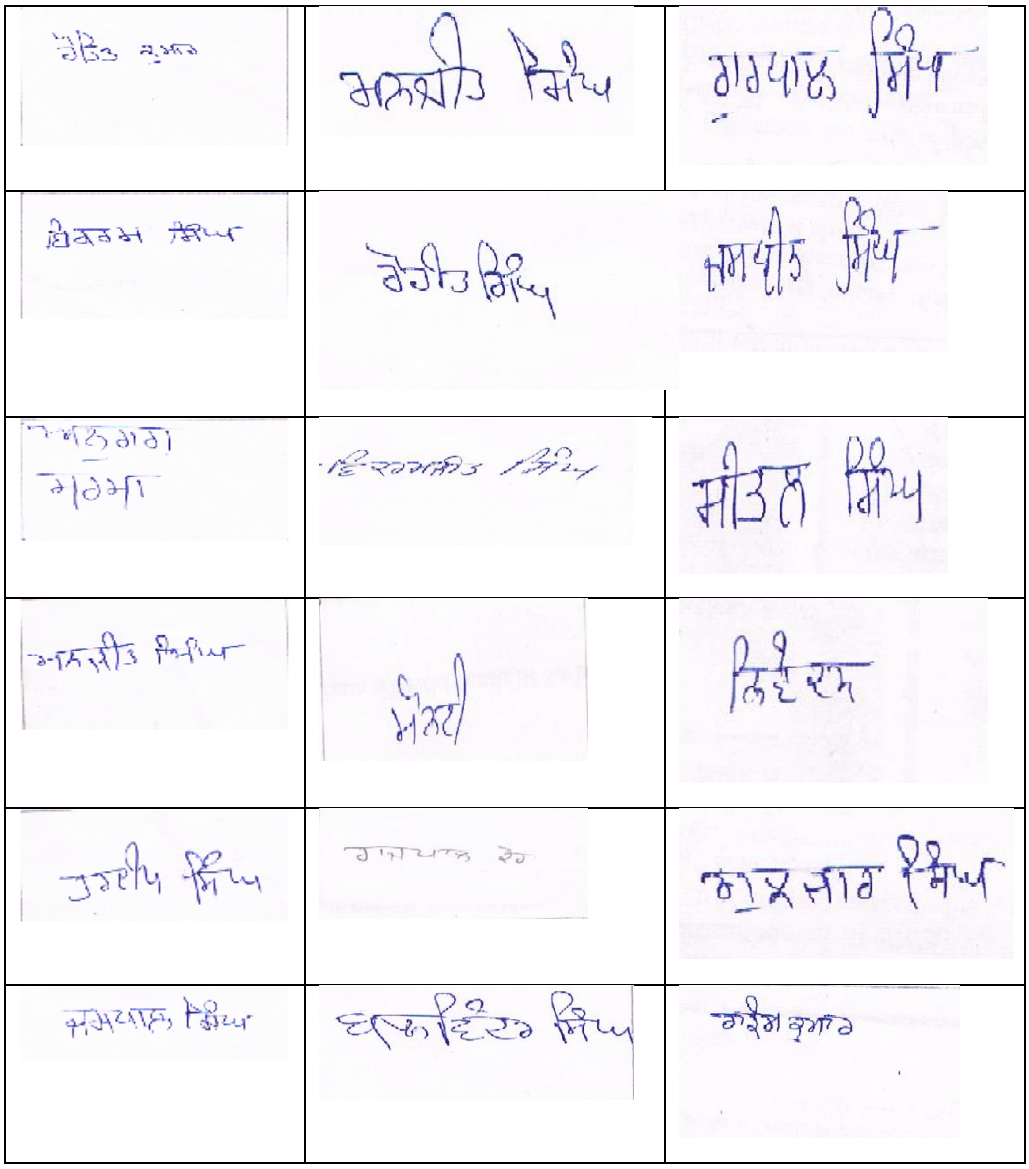


Fig 1: Database of Punjabi signatures

IV. EXPERIMENTAL STEPS AND RESULTS

In offline signature verification collecting the signature database and then scan these all signatures using the scanner. After scanning the signatures following steps performed:

Preprocessing: The first step of offline signature verification is preprocessing. The preprocessing means the improvements and the enhancement of the signature image. Various steps used under the preprocessing: Thinning is the process of reducing the shapes of objects and eliminates the thickness of the image. The handwritten signatures included a lot of noise, to reduce the noise using the median filter. Dilation of signatures image is done to compensate the small existing gaps. Then the rotation of image is used for reduce the common features between the train image and test image input.

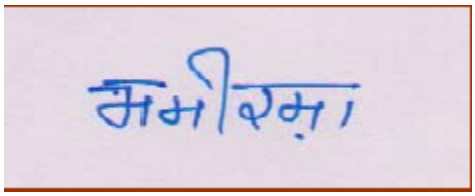


Fig 2: original signature

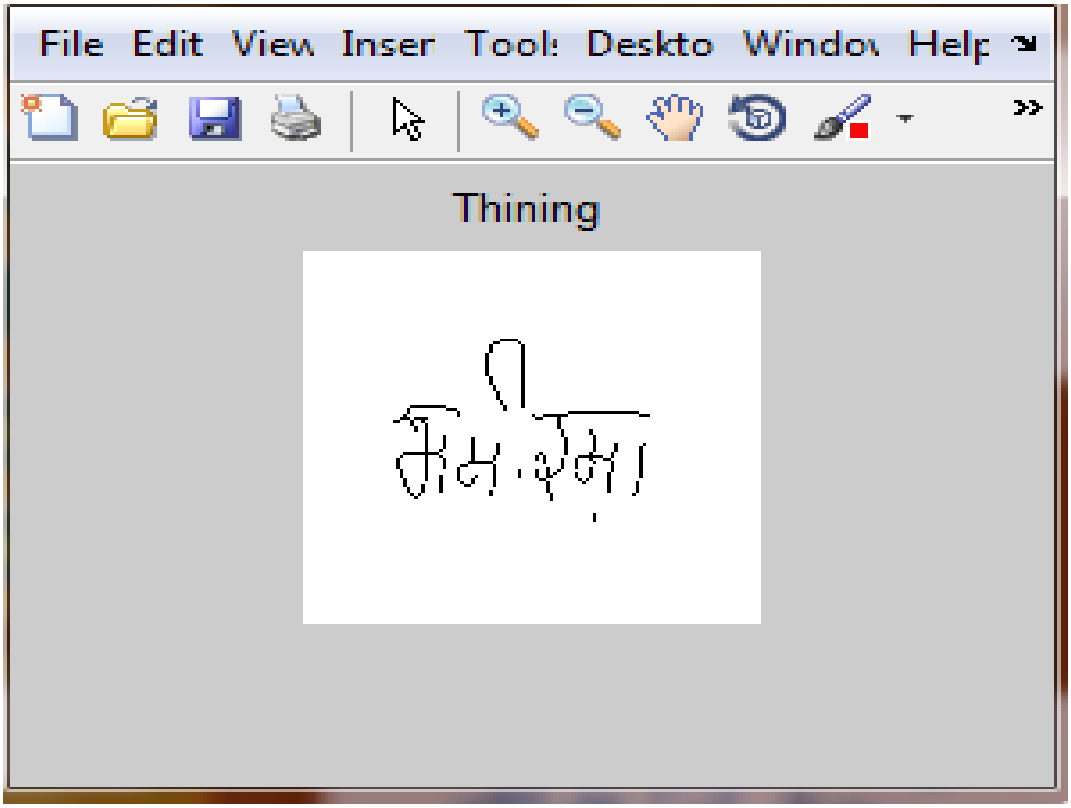


Fig3: Thinning of original signatures

Feature Extraction:

The output from the preprocessing stage is considered as input to the feature extraction stage. Feature extraction is the process of extracting the characteristic of an image and accuracy of system also depends on it. The feature extraction for offline signature verification can be divided into three categories: Global features, Geometric features, local features. In this paper we extract the geometric features. The area is the total actual number of pixels of an image. Eccentricity is the ratio of proportion of distance between the foci ellipse and length of its major axis. The kurtosis measures the flatness distribution and describes weather the data is flat or peaked. Skewness measures the asymmetry of distribution and Centriod co-ordinates are the horizontal and vertical centers of gravity of signatures. We use the Gabor filter for feature extraction. The Gabor filter is tunable band pass filter, multiresolution filter and multiscale. Gabor filter have both spatial selective and frequency selective properties.

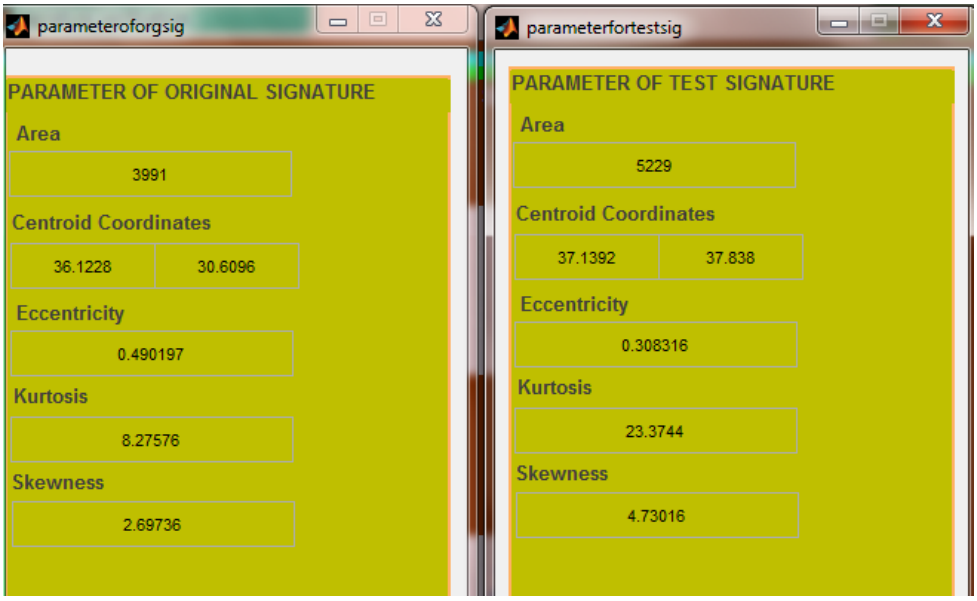


Fig 4: Geometrical Feature extraction on different parameters

Matching of signatures: To match the original signatures and forger signatures a used SURF (speed up robust features) Features and critical point matching methods. The SURF features is the invariant of SIFT. The SURF is 3-4 times fast computing speed than the SIFT. The SURF is using two algorithms for matching:

i. **Feature point detector**: It allows detecting the interest point in the image like corners and blob-like structure location. For he feature point detection using the hessian matrix approximation and firstly find out the integral of image which reduce the computation time.

ii. **Interest point descriptor:** Interest point descriptor can be divided into two different tasks firstly, every interest point is assign a reproducible orientations before a scale dependent window is constructed in which a 64-dimentional descriptor vector is extracted. Secondly, define the descriptor vector. The Haar wavelet is used for the interest point descriptor.

Critical point matching: The critical point matching is another method for matching the signatures. The contour based approach is used for feature matching. In this approach the counter is traverse and shape is changed in the curve is mark as critical points. Basically there are minimum set of points to represent the shape of Signatures**.**

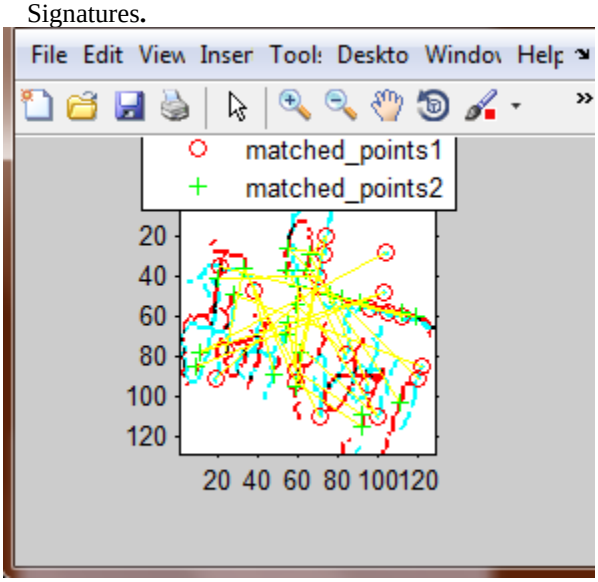


Fig 5: Matching of signatures with SURF features and critical point matching

Hidden Markov Model (HMM): A HMM is a toolbox within the Matlab environment is presented. The HMM is statistical learning model based on principal empirical risk minimization that is induction principal. The HMM is consist of N- states. Each state has two principals, the first is the nature of group of observations that associated with state and second is of histogram which describes the making of transitions. In the HMM the elements are used are:

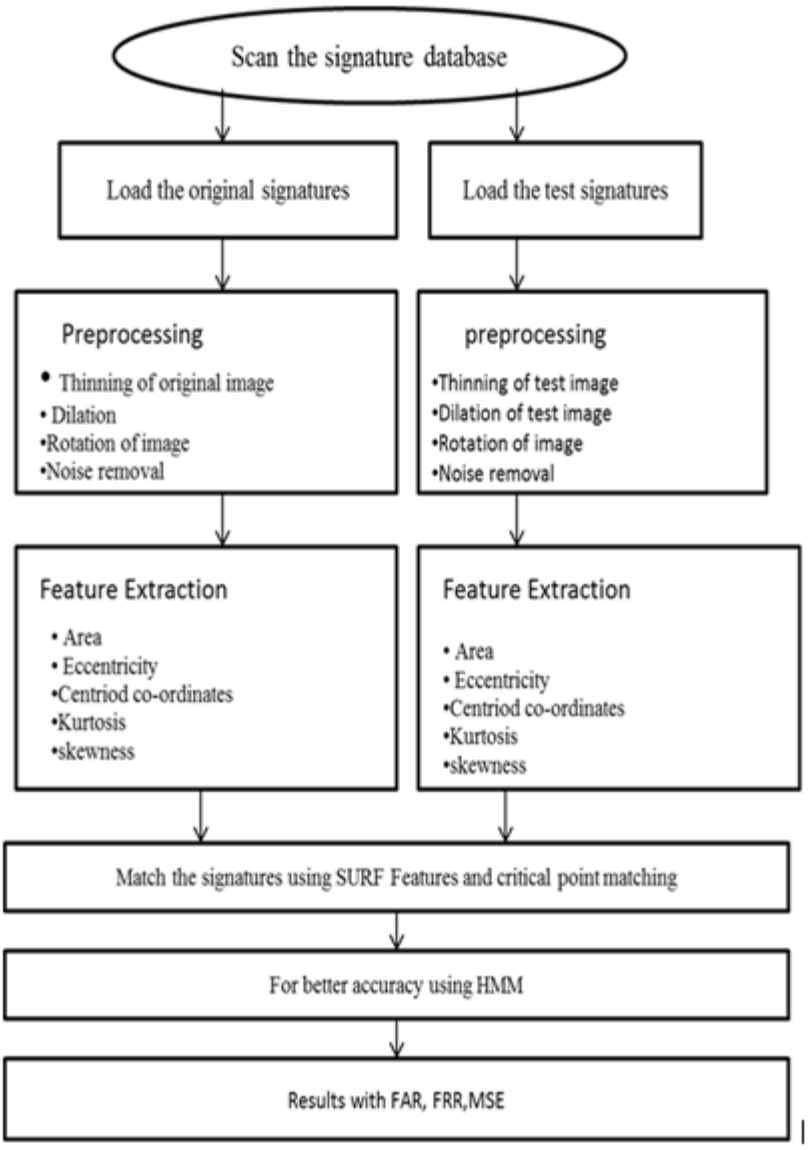


Fig 6: Steps of offline signature verification

i. Number of states (S1….S2), qi is state at T.
ii. Set of K observations symbols.
iii. State transition probability matrix (A=Aij).
V. Set of output probability distributions
VI. Initial state distributions

Resulting Parameters: In this paper the database of 200 signatures tested. The accuracy of signature identification system can be expressed by two types of errors:

False Acceptance Ratio (FAR): The FAR is given by number of forged signatures accepted by the system with respect to the total no. of comparison made.

$$FAR = \frac{\text{Total no. of forgeries accepted}}{\text{Total no. of forgeries submitted}}$$

False Rejection ratio (FRR): The FRR is the total no. of genuine signatures rejected by the system with respect to the total no. of comparison made.

$$FRR = \frac{\text{Total no. of genuine test pattern rejected}}{\text{Total no. of genuine test patterns submitted}}$$

Both FAR and FRR depends on the threshold variance parameter, taken to make a decision the genuines of an image. In this research we are taking a threshold of 90%. The network is tested and it is able of classifying the signature of taken database: genuine and forged and a classification ratio of about 97.57% is obtained.

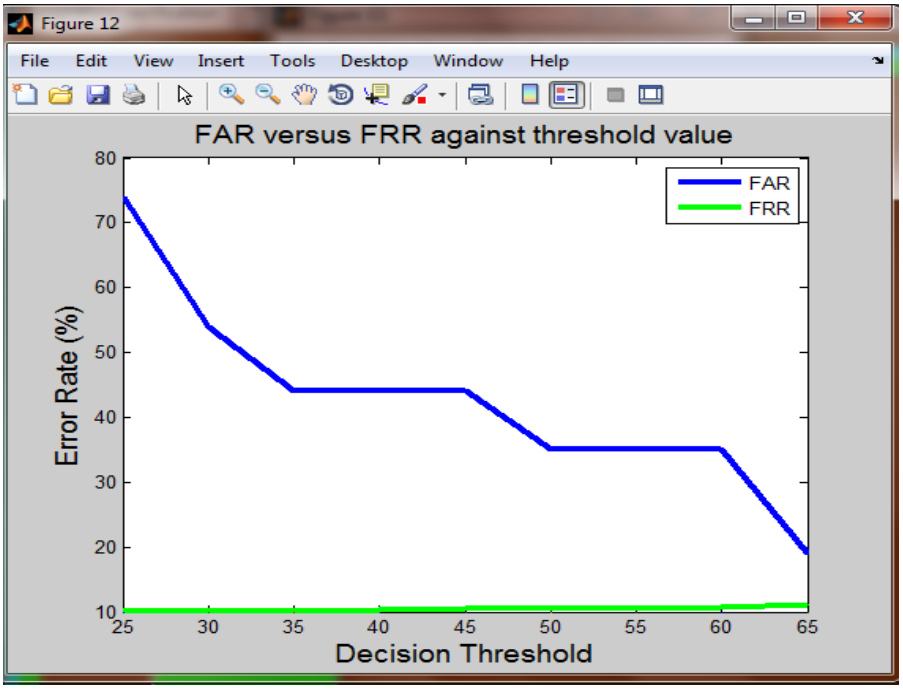


Fig 7: Results with FAR and FRR

V. CONCLUSION AND FUTURE WORK

A problem of personal verification and identification is an actively growing area of research. The techniques are based on different individual characteristics; movement, lips voice, hand geometry, face, gait, odar, iris, fingerprint and retina are the most commonly used authentication methods. Therefore considerable number of purpose is resolute in the area of electronic commerce and electronic banking systems. Many signature verification methods have been proposed previously but they were not protected enough and can be temporarily tampered with so the assignment was partial. Signature Verification with Surf feature alone could not give better results. We use Signature Verification method using HMM with surf feature. The results of matching are improved as we use HMM with surf feature technique for matching. Improved quality of signature and matching results are obtained. The offline signature identification technique and algorithm can be enhanced feature extraction and matching algorithms. There is a lot of future research work in signature identification because this work is complete only in few Indian languages.

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