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HAND WRITTEN SIGNATURE VERIFICATION USING PRINCIPAL COMPONENT ALGORITHM

A Report for evaluation 3 of project 2

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CHAPTER 1

ABSTRACT

Handwritten signature is broadly utilized as personal verification in financial institutions ensures the necessity for a robust automatic signature verification tool. This tool aims to reduce fraud in all related financial transactions' sectors. This paper proposes an online, robust, and automatic signature verification technique using the recent advances in image processing and machine learning. Once the image of a handwritten signature for a customer is captured, several pre-processing steps are performed on it including filtration and detection of the signature edges. Afterwards, a feature extraction process is applied on the image to extract Speeded up Robust Features (SURF) and Scale-Invariant Feature Transform (SIFT) features. Finally, a verification process is developed and applied to compare the extracted image features with those stored in the database for the specified customer. Results indicate high accuracy, simplicity, and rapidity of the developed technique, which are the main criteria to judge a signature verification tool in banking and other financial institutions.

CHAPTER 2
INTRODUCTION

Biometrics refers to automatic recognition of individuals based on their physiological and behavioral characteristics. The world is crying out for the simpler access controls to personal authentication systems and it looks like biometrics may be the answer. Instead of carrying bunch of keys, all those access cards or passwords you carry around with you, your body can be used to uniquely identify you. Furthermore, when biometrics measures are applied in combination with other controls, such as access cards or passwords, the reliability of authentication controls takes Giant step forward. The various application using biometrics are passports, driving licenses, banking, refraining imposters from hacking into networks, stealing mails etc. The traditional security systems are Token based system, in this fakers are prevented from accessing protected resources using ID cards, smart cards etc, Knowledge based systems, in this identity is proving by using information like user id and password associated with the system. In some system both the above mentioned approaches are used. Main advantages of biometric system over conventional approach is the reliability, it cannot be stolen or misplaced. In a biometric system various biometric features are extracting after capturing the biometric images of the user and authenticating individual by checking against the templates previously stored in the database. How an individual to be authenticated is depending upon application of the biometric system is used. The types of operating modes of biometric system are verification and identification. Till date many biometrics technique are been proposed but still in the financial sectors, administration and legal sectors relay more on the signature. A lot of researches have been performed on the signature biometric system but still more such system can be applied universally.

Traditional bank checks, bank credits, credit cards and various legal documents are an integral part of the modern economy. They are one of the primary mediums by which individuals and organizations transfer money and pay bills. Even today all these transactions especially financial require our signatures to be authenticated. The inevitable side-effect of signatures is that they can be exploited for the purpose of feigning a document’s authenticity. Hence the need for research in efficient automated solutions for signature recognition and verification has increased in recent years to avoid being vulnerable to fraud.

Signature verification can be considered a special case of pattern recognition. Like in any pattern recognition problem, in signature verification distinctive features can be extracted from a set of original signatures . however, Approaches to signature verification fall into two categories: On-line and Off-line.

On-line data records the motion of the stylus while the signature is produced, and includes location, and Online data records the motion of the stylus while the signature is produced, and includes location, velocity, acceleration and pen pressure, as functions of time. Online systems use these data captured during signing. Online systems could be used in real time applications like credit cards transaction or resource access. On the other hand, Off-line signatures are scanned from paper documents, where they were written in conventional way. Off-line Signature analysis can be carried out with a scanned image of the signature using a standard camera or scanner, and they are useful in automatic verification of signatures found on bank checks and documents.

For any legal transactions the authorization is done by the signature. So the need of the signature verification increases. The handwritten signatures are unique for individuals and which is impossible to duplicate. The technology is easy to explain and trust. The primary advantage that signature verification systems have over other type's technologies is that signatures are already accepted as the common method of identity verification. The handwritten signature verifications are of two types Online and the offline. On-line method uses an electronic technique and a computer to extract information about a signature and takes dynamic information like pressure, velocity, speed of writing etc. for the purpose of verification. In off-line signature verification involves less electronic control and uses signature images captured by scanner or camera.

An off-line signature verification system uses features extracted from scanned signature image. The features used for offline signature verification are much simpler. In this only the pixel image needs to be evaluated. But, the off-line systems are difficult to design as many desirable characteristics such as the order of strokes, the velocity and other dynamic information are not available in the off-line case. The verification process has to wholly rely on the features that can be extracted from the trace of the static signature images. In the area of Handwritten Signature Verification (HSV), specially offline HSV, different technologies have been used and still the area is being explored.

A signature is a gained behavioural biometric of a user to declare his/her unique identity on printed documents. The demand of authorization based on signature is increased including credit card validation, security systems, banking system, checks, contracts, etc. It is widely used as proof of identity and a socially accepted authentication method in daily life. The system stakeholders are person, organization or banks that need to verify signatures. The stakeholders are Bank's customers who must write their signature, and bank's employees have to verify if the sample signature is the original signature in database, to complete any transaction required on that account. Another customers are organizations' employees: any organization that still depend on paper works, employees must take supervisor's.

Automatic signature verification system compete the current visual verification that depends mainly on the experience, mood and working environment of the verifier. Moreover, it is difficult for the eyes of any experts to precisely verify the ratios between lines and angles of a genuine signature to a fraud signature. One reason is that signature is just a special way of handwriting that contains complex geometric patterns and often unreadable plots. A signature forgery is replicating the genuine signature by the forger after careful practice. This type of forgeries is called the skilled forgery which harden the signature verification task. The other two types are random forgery where the

forger does not know the shape of the original signature, and the simple forgery where the forger knows the shape of the original signature but does not practice enough to increase the similarity value between the fraud and the genuine signatures.

Automatic verification systems that authenticates the person's signature can be categorized as two types, an online (dynamic) and an offline (static) system. In online systems, dynamic data can be obtained from an online user display suchlike electronic tablet with an instructed pen and in this case, the input is a sequence of dynamic features about the user writing activity such as the applied pressure, speed of writing, etc. On the other hand, in the offline systems, signatures are written in a paper which is processed as two dimensional image and has been converted to the system with the aid of scanner or camera. The signature verification architecture usually starts by extracting the features of the genuine signatures followed by classification of a set of genuine and skilled test signatures. The offline features can be categorized as Global and local features, the Global features describe the image as whole the image size, while local features are commonly extracted by partitioning the image into a grid and extract the features in each of its parts. Lately, Interest points are picked using SIFT (Scale-Invariant Feature transform) [SIFT] and/or SURF (Speed-up Robust Features) [SIFT] to perform the signature verification task. These models extract the interest points in each image, then extract the features/ descriptors for each interest point to verify the matching between signatures. The accuracy of the solution of these methods depends on the number of matches of the genuine signatures to other genuine and forged signatures. The work proposed in this paper uses a different approach in utilizing the SIFT/SURF extractors, where the matching depends on the summing up of the Euclidian distance between the interest points in the two images. The work applied here is based on the database of offline genuine and skilled forged signatures extracted in the work in and in . The results shows 95% classification accuracy which is higher than that of current research.

Signature has been a distinguishing feature for person identification. Even today an increasing number of transactions, especially related to financial and business are being authorized via signatures. Hence the need to have methods of automatic signature verification must be developed if authenticity is to be verified and guaranteed successfully on a regular basis. Approaches to signature verification fall into two categories according to the acquisition of the data: On-line and Off-line.

On-line data records the motion of the stylus (which is also part of the sensor) while the signature is produced, and includes location, and possibly velocity, acceleration and pen pressure, as functions of time. Online systems use this information captured during acquisition. These dynamic characteristics are specific to each individual and sufficiently stable as well as repetitive.

Off-line data is a 2-D image of the signature. Processing Off-line is complex due to the absence of stable dynamic characteristics. Difficulty also lies in the fact that it is hard to segment signature strokes due to highly stylish and unconventional writing styles. The nature and the variety of the writing pen may also affect the nature of the signature obtained. The non-repetitive nature of variation of the signatures, because of age, illness, geographic location and perhaps to some extent the emotional state of the person, accentuates the problem. All these coupled together cause large intra-personal variation. A robust system has to be designed which should not only be able to consider these factors but also detect various types of forgeries. The system should neither be too sensitive nor too coarse. It should have an acceptable trade-off between a low False Acceptance Rate (FAR) and a low False Rejection Rate (FRR). The designed system should also find an optimal storage and comparison solution for the extracted feature points.

We approach the problem in two steps. Initially the scanned signature image is preprocessed to be suitable for extracting feature. Then the preprocessed image is used to extract relevant geometric parameters that can distinguish signatures of different persons. The net step involves the use of these extracted features to verify a given image.

2.1 MOTIVATION

The motivation behind the project is the growing need for a full proof signature verification scheme which can guarantee maximum possible security from fake signatures. The idea behind the project is also to ensure that the proposed scheme can provide comparable and if possible better performance than already established offline signature verification schemes.

2.2 PROBLEM STATEMENT

Signature verification and recognition is a technology that can improve security in our day to day transaction held in society. This paper presents a novel approach for offline signature verification. In this paper offline signature verification using machine learning is projected, where the signatures written on a paper are obtained using a scanner or a camera captured and presented in an image format. For authentication of signature, the proposed method is based on geometrical and statistical feature extraction and then the entire database, features are trained using machine learning. The extracted features of investigation signature are compared with the previously trained features of the reference signature. This technique is suitable for various applications such as bank transactions, passports with good authentication results etc

CHAPTER 3
EXISTING SYSTEM

In this chapter the detailed survey of current literature on signature verification based on both spatial and transform domain techniques, fingerprint verification, face recognition and bimodal biometric are presented. The literature includes a review of extraction of global and local features for signature and survey also covers offline and online signature verification. The fingerprint identification using segmentation, overview of edge detection methods, various preprocessing methods, feature extraction using FFT, DCT, DWT, DT-CWT etc., are discussed. The different face recognition methods, feature level and matching level fusion techniques are discussed.

Offline signature identification/verification

Liang Wan et al., proposed an off-line signature verification system using global features such as pure width, image area, center of signature, maximum horizontal and vertical projection, local slant angle, number of edge points and number of cross points. The verification is done using Neural Networks. Siyuan Chen and Sargur Srihari proposed an approach to off- line signature verification on contour and shape features. A sequence of data is obtained by tracing the exterior contour of the signature which allows the application of string matching algorithms. The upper and lower contours of the signature are first 26 determined by ignoring small gaps between signature components. The contours are combined into a single sequence so as to define a pseudo writing path. To match two signatures a non-linear normalization method ie., dynamic time warping is used. Shape descriptors based on Zernike moments are extracted as features from each segment. A harmonic distance is used for measuring signature similarities. Bence Kovari et al., presented off line signature verification considering the semantic information during signature comparison. The end points of strokes are identified and used as features. The dynamic time wrapping algorithm is used to measure of dissimilarities. Kai Huang and Hong Yan presented fractal transformation technique for signature verification. The signature locus is segmented onto non overlapping range segments. The features such as segment centroid, segment starting point, number of sample points in domain segment reflection transformation are extracted. Javed Ahamed Mahar et al., proposed off-line signature verification with k-NN. The grid features, global features and texture features are extracted. Since the features are uncorrelated and have different nature, the signatures are defined and evaluated using KNN classifier. Lecce et al., presented an effective procedure to select the reference specimens for a signature verification system. The dissimilarities are based on monotonicity, continuity and boundary conditions. The correlation- based measurements are used to detect and recovers non-linear time distortions in different specimens. The verification is based on a stroke orientation, signature segmentation and dissimilarity among strokes. Edson justino et al., proposed off-line signature verification using HMM. The graphometric features are extracted from segmented image. The verification is done using HMM frame work. Rigoll and Kosmala compared off-line and on-line signature verification methods. The signature stroke angles and DFT values are considered as features. The HMM is used to compare test signature features with database signature features based on vitebri algorithm. Shih-yin Ooi et al., described the off-line signature verification based on the hypothesis that each writer has similarity among signature samples with small distortion and scale variability. The discrete radon transform is applied on signature to compute features and feature set is compressed using PCA. The feature set of PCA is altered by using Gaussian distribution. The matching is done using distance formulae. Madasu Hanmandlu et al., proposed an approach for automatic off-line signature verification. The Signature angular features are extracted from box approach. The fuzzy modeling is used angular features comparisions. Stephane Armand et al., described an effective method to perform off-line signature verification using unique structural features extracted from the signature's contour. A combination of modified directional features and additional distinguishing features such as the centric, surface area, length and skew are extracted. A resilient back 28 propagation neural network and a radial basis function network are used for classification. Sudarshan Madabusi et al., proposed a relative slope based algorithm for an on-line and off-line signature verification system. The input signature is divided into segments using an optimized HMM method, then the slope of every segment is calculated with respect to its previous segment obtained after normalization of the signature and used as features. Bayes classifier is used for classification. Jun-wen chen et al.,implemented a method for off-line Chinese signature verification. The features are extracted for every segmented signature image. Every segment is represented by a set of seven features, every feature has a different effect on signature verification. Each type weighting factor is taken for similarity computation of signature verification. Piekarczyk implemented an algorithm, in which the signatures are checked for identity using graph matching. The validation is done to select the reference set of signatures. The preprocessing is used to extract exact signature to reduce EER. Samuel Audit et al., proposed off-line signature verification using virtual support vector machines. The features such as pixel density, gravity center, segment curvature and orientation are extracted. The feature vectors of each signature are classified using SVM classifier. Ramnujan Kashi and Winston Nelson have described traditional verification techniques using global features. The algorithm checks for three tries. The signature rejected in first try is checked in second and third try, if the signature 29 still fails, it is rejected as forgery. The OR logic is used for genuine and AND logic is used for forgery. Yaqian Shen et al., proposed Off-line signature verification using geometric features specific to Chinese handwriting. They presented four main features, like envelop of the signature, cross-count features, center of gravity of sub-region and distance between vectors. The decision tree and machine learning algorithms are used for signature classifications. Ming Yang et al., presented a signature verification based on contourlet. The features are extracted using contourlet transform which captures directional information. Another type of features is extracted using contour grid thought, which gives the statistical features of signature. The SVM is used to classify signature features. Hannon Coetzer and Robert Sabourin proposed an algorithm for signature verification, in which they have investigated the feasibility of utilizing both human and machine classifiers. The features are extracted using radon transform and each signature is modeled by ring structured HMM. Meenakshi Kalera et al., proposed Off-line signature verification system in which combination of gradient, structural and concavity features are extracted. These features constitute the global, statistical and geometrical features of the signature. Oliveira et al., proposed an off-line signature verification system in which graphometric features are extracted from signatures. The SVM classifier is used to classify features of signatures. The features of 30 questioned signature are compared with features of reference signatures and dissimilarity features are computed and fed to classifier, which provide practical decision. The final decision depends on the fusion of these practical decisions which are obtained through majority vote rule. Jingbo Zhang et al.,proposed a method for off-line signature verification using four group features. The extracted features include directional features, texture features, dynamic features and complexity index. The Neural Network classifier is used to verify the signature. Yu Qiao et al., proposed a framework for off-line signature verification using online signatures for registrations. The local features which describe geometric and topology characteristic of local segment such as position, tangent direction and curvature. The verification is done by using nearest neighbor classifier. Stephane Armand et al., described an effective method to perform off-line signature verification using unique structural features extracted from the signature's contour. A combination of the modified directional features and additional distinguishing features such as signature center, surface area, length and skew are extracted. A back propagation neural network and radial basis function network are used for verification. Srinivasan et al., presented an automatic signature verification method of scanned documents. The features extracted are gradient, structural and concavity features. The correlation distances between two signatures are used to classify signatures. Ozgunduz et al., developed an off-line signature 31 verification and recognition system using the global, directional and grid features of signatures. The SVM is used to verify and classify the signatures and its performance was compared with artificial neural network's back propagation method in terms of success ratio and ease of implementations. Ueda investigated off-line Japanese signature verification system using pattern matching method, thus strokes of signature are thinned and blurred by a fixed point spread function. The mean and standard deviation of features of signature samples are computed. The signature with maximal ratio of mean and standard deviation is considered as Genuine. Wan Liang et al., proposed an off-line signature verification using integrated classifiers based on global, grid, ink distribution and texture features. The Boosting algorithm is applied to train and integrate multiple classifiers. The distance-based classifier is used as the base classifier corresponding to each feature set for verification. El-Yacoubi et al., proposed a HMM based off-line signature verification system. The method extracts features such as pixel density, signature height, width spacing and graphometric features. Verification is done by using HMM model. Nabeel Murshed et al., presented an off-line signature verification system. The features are extracted based upon predefined grid for each user and geometric center based on identity grid. Matching is done using Fuzzy logic. Kulkarni proposed an image processing technique to verify signature instantly. The system deals with a Color 32 Code algorithm to recognize the signature, which is usually done by the human operator. The algorithm simulates human behavior to achieve perfection and skill through Artificial Intelligence. The check patterns for both the standard signature and the test signature are generated by considering their centroids and Exclusive-OR operation is used for comparison. Zhong-Hua Quan and Kun-Hong Liu proposed an online signature verification system. The hybrid HMM/ANN model is constructed by using a time delay Neural Networks (NN) as local probability estimators for an HMM. The local time function of test signature and template signature are computed other that HMM/ANN model for verification. Hao Feng and Chan Choong Wah proposed an Extreme Point Warping (EPW) technique for signature verification instead of Dynamic Time Warping (DTW). EPW warps a set of selective points that is the Extreme Points (EPs) on the signal rather than the whole signal. This preserves the local curvatures between the EPs, which prevent forged signals taking advantage from the warping process. The EPW is more adaptive than DTW in the presence of the forgeries. Hui Jiang and Chong-Wah Ngo introduced a graph matching based approach to solve the problems on pattern matching. The image is split into small blocks and each block is represented as a node in a bipartite graph. A maximum weighted bipartite graph-matching algorithm is then employed 33 in an iterative way to find the best transformation set. This method is invariant to rotation, scaling, translation and distortion.

Fingerprint Verification

Dale and Joshi proposed a fingerprint matching based on transformed co-efficient. The coefficient of DCT, FFT and DWT are used as features of fingerprint. The standard deviation is computed for these features and considered as feature vectors. The verification is done using Euclidean Distance (ED). Dadgostar et al., initiated a fingerprint identification method, in which features are extracted using Gabor filter and Recursive Fisher Linear Discriminant (RFLD) algorithms. The features extracted by Gabor filter are usually high dimensional. The RFLD algorithm is used to reduce dimensions of features. The NN classifier and nearest cluster center point classifiers are used for matching. Umair Mateen Khan et al., discussed a fingerprint matching criteria. The features extracted from both minutiae based method and wavelet transformation based method is added to improve results. Zhou Weina et al., described an algorithm combining wavelet transform with Prewitt edge detection for fingerprint verification. The fingerprint verification is based on the features extracted using wavelet's and prewitt edge detection's stable characteristics in translation, scaling and rotation. Leon et al., developed algorithms for image enhancement and the invariant moments in the verification phase. The 34 fingerprint verification is based on combination of FFT and Gabor filters with image enhancement. A thinning algorithm is applied to get an image with minimum thickness of one pixel. The feature vector is generated by the distance between minutiae, the angle between minutiae and coordinates. Bhowmik et al., derived a minutiae matching algorithm using smallest minimum sum of closest ED. The matched minutiae pairs from input and template fingerprints based on corresponding rotation angle and empirically chosen statistical threshold values. The method reduces an effect of non-linear distortion using only minutia locations. Helfroush and Mohammadpour developed a method for fingerprint verification system which does not need any reference point and preprocessing. The features are extracted using all pixels of fingerprint images. The final feature vectors are based on the fusion of spectral and directional features. Javed Ahmed Mahar and Syed Faisal Ahmed Bukhari presented a robust automated system for the verification of fingerprints. The core point is features which are determined by identifying maximum curvature of concave ridges in fingerprint image and circular grids. The region of feature extraction was filtered in eight different directions by using Gabor filters. The absolute difference vector technique was used to compare features. Shan Juan Xie et al., designed a Region of Interest (ROI) based quality estimation system for fingerprint recognition system. The ROI is determined by new orientation certainty value before the quality 35 estimation. The features such as image consistency and local orientation quality are computed to evaluate the ROI. Nae Myo developed an accurate and secure fingerprint verification method. The fingerprint is segmented and features are extracted based on the dominant brightness values of the fingerprint. Amornraksa and Tachaphetpiboon proposed fingerprint recognition using DCT features. The method consists of finding the reference point and cropping an image to 64*64 size centered around reference point. The image thus obtained is quartered into four non-overlapping images of size 32*32 pixels. The DCT is applied on each quartered image and standard deviations from 6 nonoverlapping regions are considered as feature vectors. Haiyun Xu et al., discussed a method to represent a minutiae set as a fixed-length feature vector. The location-based spectral minutiae representation and orientation-based spectral minutiae representation are applied and the results are fused. The correlation based minutiae matching algorithm is used for verification. Jun Ma et al.,proposed an effective algorithm for fingerprint verification system. Poincare index on the block level is used, which was combined with the adaptive smoothing for getting a better orientation map and the directional consistency factor with an purpose of choosing the correct block. The center pixel of selected block is reference point used for verification. Conti et al., derived fingerprint classification method and a matching algorithm based on fingerprint topological information. The features 36 extracted are core and delta or pseudo-singularity point's position, their relative distance and orientation are used for classification and verification. Dass developed an algorithm for quantitative study on an effect of noise in minutiae detection and localization. The measure of fingerprint individuality was modeled as a function of image quality via a random effects model and methodology for the estimation of unknown parameters is developed in Bayesian frame work. Zhang Yuanyuan and Jing Xiaojun proposed an algorithm of fingerprint verification. The image is enhanced using the Gabor filter. The gabor filter parameters are computed in both spectral and spatial domain. The images are filtered in frequency domain using filtering function. Chomtip Pornpanomchai and Apiradee Phaisitkulwiwat proposed the fingerprint recognition based on position of the core point and bifurcation points. The shape context of training and testing data sets are compared using ED. Keming Mao et al.,proposed an algorithm for fingerprint image enhancement. The fingerprint image is enhanced using Gabor filter. The orientation field and ridge frequency of fingerprint are computed. After the parameters are tuned, the region is regulated according to an orientation and frequency of local ridges. The filtering was implemented in one quadrant region instead of whole region, since Gabor filter is even symmetric. Xuejing Jiang et al., suggested an algorithm for fingerprint recognition. The image is located by using RFID Readers and tags. The image located and the distribution of Received Signal Strength Indicator (RSSI) is 37 calculated. The RSSI is different at each point for the same image. The probability model is framed by taking RSSI values for the image. Hendrik Lemelson et al.,proposed a method to find the location of fingerprint image in the database. The areas of operation are split into a grid of quadratic cells and then combine these cells into larger regions of similar signal properties using a clustering algorithm and similarity measure. The area of operation is scanned on predefined trajectories and interpolates the approximate position for each measurement. Keokanlaya Sihalath et al., defined a technique to enhance the quality of fingerprint images by using directional wavelet transform and second derivative of a Gaussian filter. The image is decomposed into approximation and detail sub-images. The enhanced image is measured for its improvement by testing the success of core point identification. Aliaa et al.,developed an automatic fingerprint recognition system based on hybrid between minutiae and correlation based techniques to represent and to match fingerprint. The hybrid approach is an improvement of minutiae extraction algorithm. The ridge algorithm uses center point of fingerprint instead of reference point. Yi Wang and Jiankun Hu defined a method for identifying incomplete or partial fingerprints. The partial fingerprints are identified using one-to-one matching with local ridge details. An inverse orientation model describe the reconstruction, which allows preserving data fidelity in an existing segments while exploring missing structures in an unknown parts. 38 Ashwini Patil and Mukesh Zaveri suggested a fingerprint recognition system, in which matching is done using Pattern recognition based on minutia features. For minutia marking, false minutiae removal and for minutiae matching, alignment based methods are used. Yanan Meng proposed an improved adaptive preprocessing method for fingerprint Image. The given replicated archetypes, multi-processors are used to get the features of fingerprint images. Yunye Jin et al., derived the theoretical error probability density function and region of confidence conditioned on the on-line signal parameter vector for a fingerprint-based localization system. The computations of these terms require the exact expression of joint density function for both the device location and the on-line signal parameter vector. The nonparametric kernel density estimation techniques are used for training fingerprints. Radu Miron and Tiberiu Leţia proposed fingerprint recognition systems using minutiae matching algorithms. This technique is widely used because of the temporal performances. The complete fingerprint matching is by core-minutiae-based structure. A fuzzy logic algorithm based on correlating a minutiae set and regions between ridges are for matching partial fingerprints. Chao Chen et al., discussed segmentation of image for fingerprint recognition. Segmentation is done in order to preserve genuine and reduce false minutiae and increases the performance of automatic fingerprint identification system. A simple and efficient segmentation of fingerprint image is based on the polarimetric 39 variance. The polarimetric characteristic is a feature other than reflecting light carries, and it enhance the contrast between background and foreground, between ridges and valleys. Non overlapping block Polvar features are used for faster computation. Yi Hu et al., proposed fingerprint enhancement to improve the ridges and eliminate the noises. Gabor filter is the preferred enhancement method, performance reduces for low quality images due to unreliable orientation and frequency map estimated by conventional approach. To increase the performance, enhancement is done by applying short time fourier transform on the local image which is modeled as a non stationary signal. Jiaojiao Hu and Mei Xie proposed an algorithm for fingerprint classification. The algorithm classifies a fingerprint image as arch, left loop, right loop, whorl, and tented arch. The preprocessing of fingerprint images are carried out to enhance an image. The genetic programming is used to generate features from the original dataset. Raffaele Cappelli et al., introduced the minutia cylinder-code, which is a representation based on 3D data structures obtained from minutiae distances and angles. The cylinders are created using subset of the mandatory features such as minutiae position and direction. By using cylinder invariance, fixedlength and bit-oriented coding, effective metrics is created to compute local similarities and consolidate them into a global scores. Hengzhen Gao et al., discussed identification of singular points in the ridge structure for fingerprint matching. The fingerprint singular point 40 detection is used for various fingerprint images of different resolutions. The singular points are extracted using the Discrete Hodge Helmholtz Decomposition (DHHD) and Poincare Index (PI) of an image. The combination of DHHD and PI are used to detect singular points. Wang Wenchao and Sun Limm discussed a fingerprint identification algorithm that combines point match and image match. This algorithm depends on singular point abstraction and wavelet transform coefficient. First singular points are extracted for rough match and image calibration. Ma Yinping and Huang Yongxing introduced a kind of wavelet transform adaptive threshold of the fingerprint image denoising method. The approach is one of the fingerprint image wavelet decomposition and then based on Bayes framework, selecting different optimal threshold, combined with a soft threshold value method to fingerprint image denoising, improve the fingerprint image Peak Signalto-Noise Ratio. Balti et al., proposed an improved features for fingerprint identification algorithm based on ED between the center point and their nearest neighbor bifurcation and ridge ending minutiae's which reduces the problem of geometric rotation and translation over the acquisition phase of image fingerprints.

Face Recognition and Bimodal biometrics

Zeenathunisa et al., proposed a biometric identification system for frontal static face image subjected in various dark illuminations. An automatic face recognition biometric system has been developed using 41 Local Binary Pattern (LBP) and KNN classifier. Jinxia Ni and Zhongxi Sun implemented inverse fisher discriminant analysis for face recognition. The intrinsic features are characterized using Gabor wavelet transform and image discriminant features are extracted by selecting principal components and inverse fisher discriminant vectors. Seyed Omid Shahdi and Abu-Bakar proposed a method to recognize nonfrontal faces with high performance by relying only on single full frontal gallery faces. The fourier coefficients are used as feature vectors. The vectors are used to estimate the frontal face vectors and then compare it with the actual frontal feature vectors. Ngoc-Son Vu and Alice Caliper described Patterns of Oriented Edge Magnitudes (POEM) i e., recent feature descriptor. The POEM parameters are optimized and then applied to the whitened PCA to get a more compact, robust, and discriminative descriptor. For face recognition, the efficiency of an algorithm is strong for both constrained and unconstrained data sets in addition with the low complexity. Shih-Ming Huang and Jar-Ferr Yang implemented a face recognition framework using improved principal pomponent regression classification algorithm, which overcome the problem of multi collinearity in linear regression. The first principal components are intentionally dropped to boost the robustness against illumination changes. Reza Ebrahimpour et al., proposed a face recognition method in which the first four different representation of face are generated using Gabor filters which vary in angles. Base classifier is 42 assigned for each of them and also for original image. Finally EMV technique combines the Base-classifiers. Biggio et al., have investigated the robustness of different score fusion rules for multimodal biometric verification systems, against spoofing attacks for fingerprint and face biometrics. The simulated worst-case scenario considered is not representative of the score distribution of real spoofing attacks. Abhishek Nagar et al., discussed a feature-level fusion framework for the design of multi biometric cryptosystems that simultaneously protects the multiple templates of a user using a single secure sketch.

The feasibility of such a framework has been demonstrated using both fuzzy vault and fuzzy commitment. Arun et al., proposed the feature extraction techniques for three modalities viz. fingerprint, iris and face. The extracted information from each modality is stored as a template. The information is fused at the match score level using a density based score level fusion, Gaussian Mixture Model (GMM) followed by the Likelihood ratio test. Hayet Boughrara et al.,have proposed an algorithm to overcome an variations of facial expression and a biological vision-based facial description Perceived Facial Images (PFIs), applied to facial images for 2D face recognition. Based on the intermediate facial description, SIFT-based feature matching is then carried out to calculate similarity measures between a given probe face and the gallery ones. Sangita Bharkad and Manesh Kokare [104] have proposed an M-band wavelet 43 transform based feature extraction technique for fingerprint matching. A combination of standard deviation and energy features are used to form feature vector. ED and city block distance metrics are used to compute the similarity between database images and test image. City block distance gives the better performance over ED as it computes the difference at each dimension instead, the square at each dimension of feature vector. Mohammad O Derawi et al., described a multimodal biometric authentication approach using gait and fingerprint images as biometric character. The individual comparison scores derived from the gait and fingers are normalized using z-score, median absolute deviation, tangent hyperbolic and fusion approaches applied are simple sum, user-weighting, maximum score and minimum score. Carsten Gottschlich defined a curved Gabor Filter that locally adopts their shape to the direction of flow. This curved Gabor Filter enable the choice of filter parameters that increase the smoothing power without creating artifacts in the enhanced image. The curved Gabor Filters are applied to the curved ridge and valley structures of low-quality fingerprint images. The two orientation fields are combined in estimation methods in order to obtain a more robust estimation for very noisy images. The curved regions are constructed by following the respective local orientation which are used in estimating the local ridge frequency. Muhammad Faysal Islam and Nazrul Islam implemented system architecture for mobile device security and user authentication applying biometrics.

The 44 proposed architecture can be applied in various mobile platforms without requiring dedicated biometric scanners and can also enhance protection against intrusion, theft and manipulation of mobile devices. Hailong Jia and Pei Tang proposed the image segmentation algorithm for fingerprint. Comparing to the original segmentation algorithm of variance method, amount of calculation is increased, but can effectively cut the background area and noise area with low quality off, to make the processing area of subsequent algorithm more precise. The wavelet transform is applied to compute features. Annan et al., proposed a method for cross-pose face recognition using a regressor with a coupled bias–variance tradeoff. The striking coupled balance between bias and variance in regression for different poses could improve the regressorbased cross-pose face representation. When enhanced with Gabor features around some key facial land- marks, the performance could be close to the state of the art. The performance of recognizing faces across poses may be further improved by exploring more complicated models for bias–variance balancing. Rajeswari Mukeshi and Subashini proposed fingerprint recognition system using threshold visual cryptographic techniques. The fingerprint template is divided into two or more shares by visual cryptographic technique followed by compression. One of these shares are stored into the server and the remaining shares are given to the users. Only these two participants who possess these transparencies can reconstruct the secret by superimposition of shares. 45 Ravi et al., proposed face recognition system using DT-CWT and LBP Features for different databases. The DT-CWT is applied on face images to generate coefficients. The DTCWT coefficient matrix is segmented in to 3*3 matrix. The LBP is applied on each 3*3 matrix to obtain final features. The ED is used for matching. Marwa et al., designed a hybrid approach for face recognition system based on GPU implementation using wavelet transformation and principle component analysis. Recognition using the wavelet transform and the PCA algorithm improve the recognition accuracy, besides minimizing time of processing. Ruiz-Echartea et al., proposed segmentation strategy based on the gradient magnitude of an image and the detection of regions. The proposed strategy uses magnitude of the gradient with the aim of detecting abrupt changes in intensity of an image. Binarizing the image, the region of the fingerprint becomes more notable which makes detection easy by applying a mean to obtain regions with uniform intensity. The binarization allows detecting all the regions that conforms the image, small regions are discarded while the largest belonging to the fingerprint are retained. Olegs Nikisins and Modris Greitans developed an adaptation of the LBP operator for the design of an automatic face recognition algorithm. The automatic face recognition process is divided into three main stages: face detection, face localization and face recognition. The approach for the realization of all these stages based on a single LBP transform. Prabhu Teja and Ravi proposed a 46 subspace framework Bi-Directional Principle Component Analysis (BDPCA) plus Linear Discriminant Analysis (LDA) for better recognition. LDA in the BDPCA subspace, compared to any subspace feature extraction method, BDPCA+LDA requires less computational and memory needs and can achieve competitive recognition accuracy. BDPCA+LDA is an LDA approach that is applied on a low-dimensional BDPCA subspace, and thus can be used for fast facial feature extraction. Soweon Yoon et al., discussed a method called automated fingerprint identification systems. The algorithm automatically detects altered fingerprints based on the characteristics of the fingerprint orientation field and minutiae distribution. The algorithm based on the features extracted from the orientation field and minutiae satisfies the three essential requirements for alteration detection algorithm, fast operational time, high true positive rate at low false positive rate, and ease of integration into AFIS. Jinhai Zhang invented the theory and methods of fingerprint image segmentation which is the important step in fingerprint image preprocessing. Fingerprint image segmentation method is based on pixel and Gabor filter. The improved algorithm for segmentation is using linear classifiers and logistic regression model based segmentation. Zhiwei Zhang et al., proposed a Regularized Transfer Boosting algorithm named R-TrBoost, with features of weighted loss optimization equation and manifold regularization to enforce label/ score smoothness. R-TrBoost solve the problem of multispectral 47 face detection by combining existing large scale visible face images and a few multi- spectral face images. Qijun Zhao and Anil Jain proposed a model based method for separating overlapping latent fingerprints. The algorithm reconstructs the orientation field of overlapping fingerprints based on a set of manually marked features, including regions of interest, singular points, and orientation cues. Fingerprint orientation field models have been widely used for regularizing the estimation of fingerprint ridge orientation field and predict unknown orientations. Rattani et al., proposed an algorithm for bimodal biometric using feature level fusion. The face and fingerprint are considered for recognition. The Scale Invariant Feature Transform (SIFT) features are computed for face and minutiae features are extracted for fingerprint. The features extracted are concatenated to compute the final result. The matching score is computed using point pattern matching where spatial distance, direction distance and the ED are computed. Shekhar Karanwal et al., proposed an algorithm for bimodal biometric in which face and fingerprint are fused. The face image and fingerprint are decomposed using DWT, the decomposed images are fused and SIFT features are extracted from the fused image. After extracting SIFT features, matching is performed by computing dot product between unit vector. Gian Luca Marcialis and Fabio Roli proposed an algorithm for bimodal biometric, in which face and fingerprint are considered. The features of face are extracted using PCA 48 and the minutia based features are extracted for fingerprint. Matching is computed individually using ED. The match score is fused and evaluated based on acceptable threshold. Huytho Ho and Chellappapresented a method for reconstructing the virtual frontal view from a given non frontal face image using Markov random fields and an efficient variant of the belief propagation algorithm. The input face image is divided into a grid of overlapping patches and a globally optimal set of local warps is estimated to synthesize the patches at the frontal view. A set of possible warps for each patch is obtained by aligning it with images from a training database of frontal faces. The alignments are performed efficiently in the fourier domain using an extension of the Lucas-Kanade algorithm that can handle illumination variations. Huang Shih-Ming and Yang Jar-Ferr proposed a face recognition system in which a Linear Discriminant Regression Classification (LDRC) algorithm is used to boost the effectiveness of the Linear Regression Classification (LRC) for face recognition. The fisher criterion is embedded into the LRC as discriminant regression analysis method. The LDRC attempts to maximize the ratio of the between-class reconstruction error over the within-class reconstruction error to find an optimal projection matrix for the LRC, such that the LRC on that subspace can achieve a high discrimination for classification. 49 Marsicoet al., proposed a framework for real-world face recognition in uncontrolled settings named Face Analysis for Commercial Entities (FACE). The normalization strategies to address pose and illumination variations are used. Two image quality indices quantitatively assess pose and illumination changes for each biometric query, before submitting it to the classifier. The poor quality images are discarded or undergo a manual classification. A template similarity for matching purposes is measured using a localized version of the image correlation index. Mohammadzade et al., proposed a common approach for 3D face recognition. It is to register a test face to each of the database faces and to calculate the sum of the distances between their points. The iterative closest normal point method for finding the corresponding points between a generic reference face and every input face is introduced. These points are effectively aligned across all faces, enabling effective application of discriminant analysis methods for 3D face recognition. The expression variation problem is addressed by minimizing the within-class variability of face samples while maximizing the between class variability. The surface normal vectors of the face at the sampled points contain more discriminatory information than the coordinates of the points.

CHAPTER 4

PROPOSED METHODOLOGY

In this section, block diagram of system is discussed. Fig. 3.1 gives the block diagram of proposed signature verification system which verifies the authenticity of given signature of a person. The design of a system is divided into two stages;

A) Training stage

B) Testing stage

- **Training Stage**

  Consist Of Four Major Steps

  i. Retrieval of a signature image from a database

  ii. Image pre-processing

  iii. Feature extraction

  iv. Neural network training.
- **Testing Stage**

  Consists Of Five Major Steps

  i. Retrieval of a signature to be tested from a database

  ii. Image pre-processing

  iii. Feature extraction

iv. Application of extracted features to a trained neural network

v. Checking output generated from a neural network.

CHAPTER 5

Flow Diagram

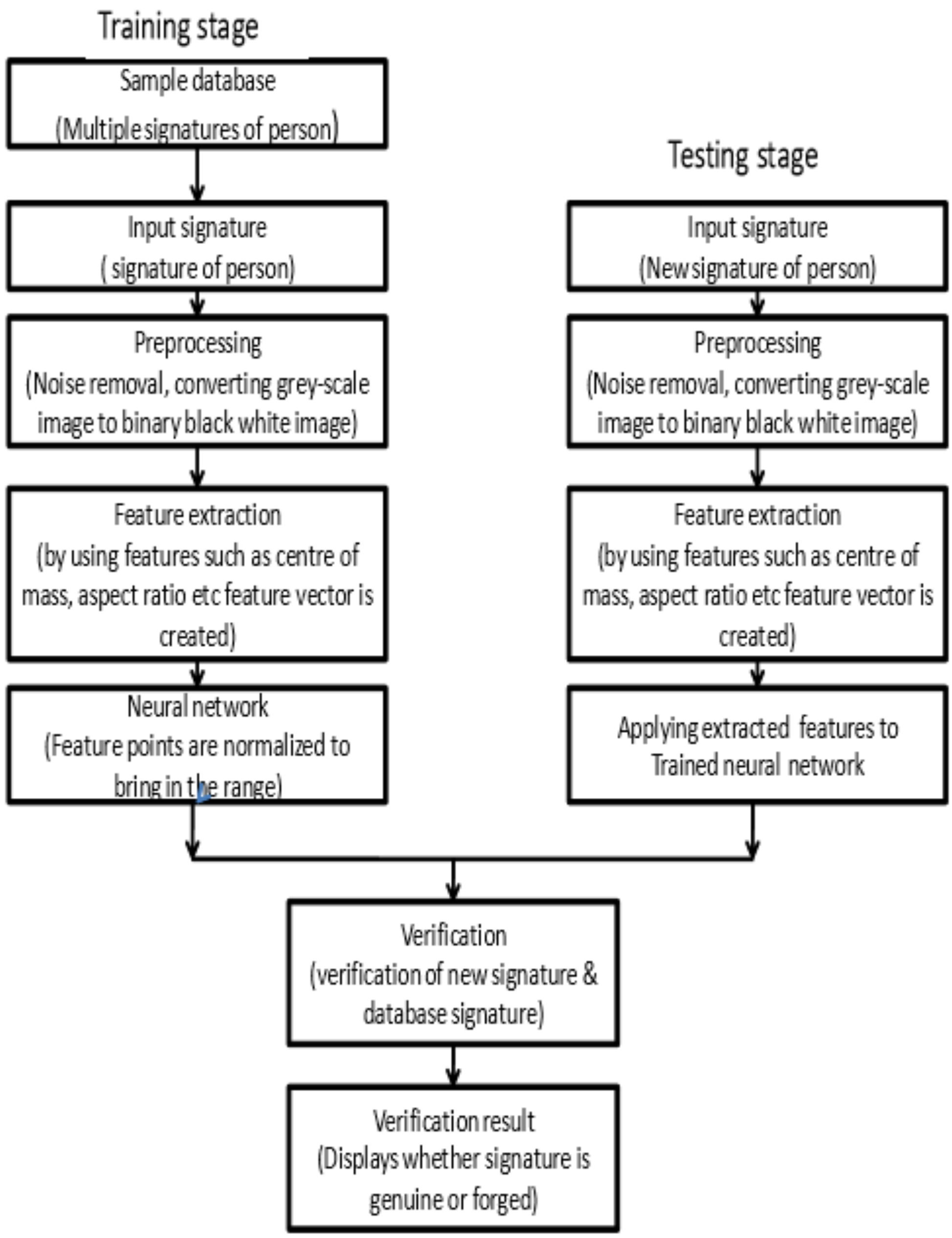

Figure 3.1: Flow Chart

5.2 Block Diagram:

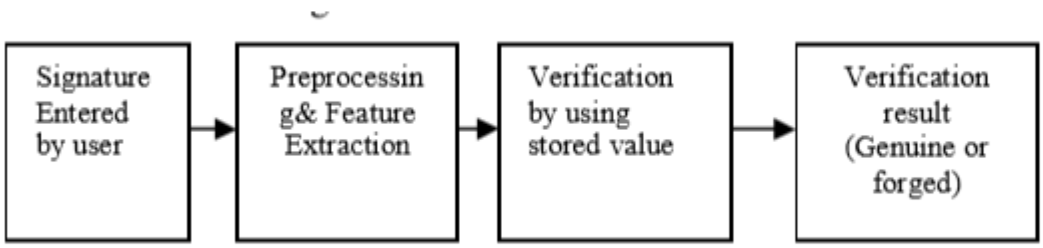

Figure 3.2: Block Diagram

Figure5.3: Signature Image from the database

Fig.5.3 shows one of the original signature image taken from a database and all the subsequent figures show the resultant signature image obtained after performing the steps mentioned in an algorithm. The pre processing step is applied both in training and testing phases. Signatures are scanned in gray. The purpose in this phase is to make signature standard and ready for feature extraction. The pre-processing stage improves quality of the image and makes it suitable for feature extraction. The prepossessing stage includes. A gray scale signature image is converted to binary to make feature extraction simpler. The signatures obtained from signatory are in different sizes so, to bring them in standard size, resizing is performed, which will bring the signatures to standard size 256*256 as shown in Fig. 3.3. Thinning makes the extracted features invariant to image characteristics like quality of pen and paper. Thinning means reducing binary objects or shapes to strokes that are single pixel wide. In the signature image, construct a rectangle encompassing the signature. This reduces the area of the signature to be used for further processing and saves time. The choice of a powerful set of features is crucial in signature verification systems. The features that are extracted in this phase are used to create a feature vector. A feature vector of dimension 24 has been used to uniquely characterize a candidate signature. These features are extracted as follows:

A. Maximum horizontal and vertical histogram

Horizontal histogram is calculated by going through each row of the signature image and counting number of black pixels. A row with maximum number of black pixels is recorded as maximum horizontal histogram. Similarly, a vertical histogram is calculated by going through each column of the signature image and finding a column with maximum number of black pixels.

B. Center of Mass

Split the signature image in two equal parts and find center of mass for individual parts.

C. Normalized area of signature

It is the ratio of area of signature image to the area of signature enclosed in a bounding box. Area of a signature is the number of pixels comprising it.

D. Aspect Ratio

It is the ratio of width of signature image to the height of the image. This is done because width or height of person's signature may vary but its ratio remains approximately equal.

E. Tri surface feature

Two different signatures may have same area .so; to increase the accuracy of the features three surface feature has been used.

F. The six fold surface feature

Divide a signature in three equal parts and find bounding box for each part. Then calculate centre of mass for each part. Draw a horizontal line passing through centre of mass of each part and calculate area of signature above and below centre of mass within a bounding box. This provides six features.

G. Transition feature

Traverse a signature image in left to right direction and each time there is a transition from 1 to 0 or 0 to 1, calculate a ratio between the position of transition and the width of image traversed and record it as a feature. Repeat a same process in right to left, top to bottom and bottom to top direction. Also calculate total number of 0 to 1 and 1 to 0 transitions. This provides ten features.

CHAPTER 6

ALGORITHM

Input: signature from a database Output: verified signature classified as genuine or forged

1. Retrieval of signature image from a database.
2. Pre-processing the signatures.
3. Converting image to binary.
4. Image resizing.
5. Thinning.
6. Finding bounding box of the signature.
7. Feature extraction
8. Maximum horizontal and vertical histogram
9. Centre of mass
10. Normalized area of signature
11. Aspect ratio
12. The tri surface feature
13. The six fold surface feature

14. Transition feature

15. Creation of feature vector by combining extracted features.

16. Normalizing a feature vector.

17. Training a neural network with a normalized feature vector.

18. Steps 1 to 17 are repeated for testing signatures.

19. Applying normalized feature vector of test signature to trained neural network.

20. Using a result generated by the output neuron of the neural network declaring a signature as a genuine or forged.

CHAPTER 8
RESULT AND DISCUSSION

For training and testing of the system many signatures are used. The results provided in this research used a total of 1000 signatures. Those 1000 signatures are comprised of 100 sets (i.e. from 100 different people) and, for each person there are 5 samples of genuine signatures and5 samples of forgeries. To train the system, a subset of this database was taken comprising of 5 genuine samples taken from each of the 100 different individuals and 5 forgeries made by different person for one signature. The features extracted from 5 genuine signatures and 5 forged signatures for each person were used to train a neural network. After applying a feature vector of test signature if the output neuron generates value close to +1 test signature is declared as genuine or if it generates value close to -1 it is declared as forged. The Accuracy of system is 86.25%

8.1 Accuracy of the proposed model

The proposed model is applied on two benchmark datasets. For the first dataset the results in figure 4.1 and 4.2 show that, the first 4 points are genuine-genuine matchings, while the rest of the points are genuine-forged matchings. In this test, 30 forged signatures are tested for verification of signatures of user one and user two. The defined threshold here is applied as the two points out of four which have the lowest Euclidian distance. Accordingly, the results shows nearly 85% classification accuracy of proving the forgery of user one and 92% classification accuracy for user two, as displayed in figure 4.1 and figure 4.2; respectively. Note that these results are based on the Euclidian distance values, not based on the number of matchings

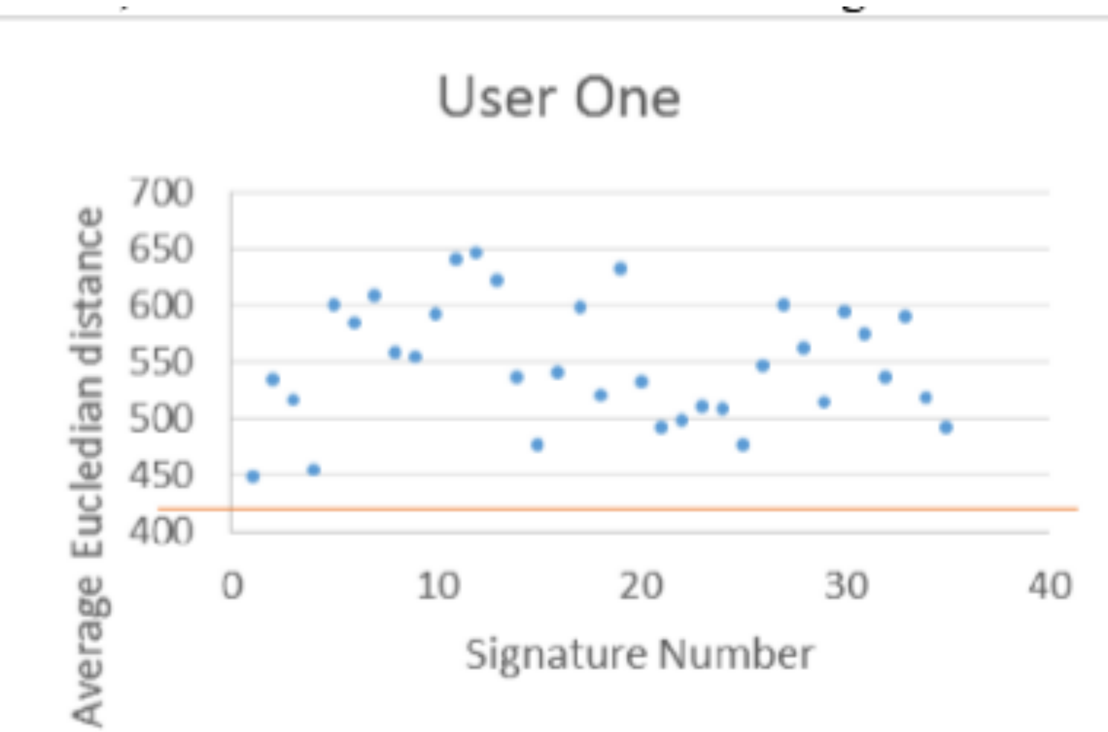

Fig. 8.1. Genuine-Genuine vs Genuine-Forged signatures for user one

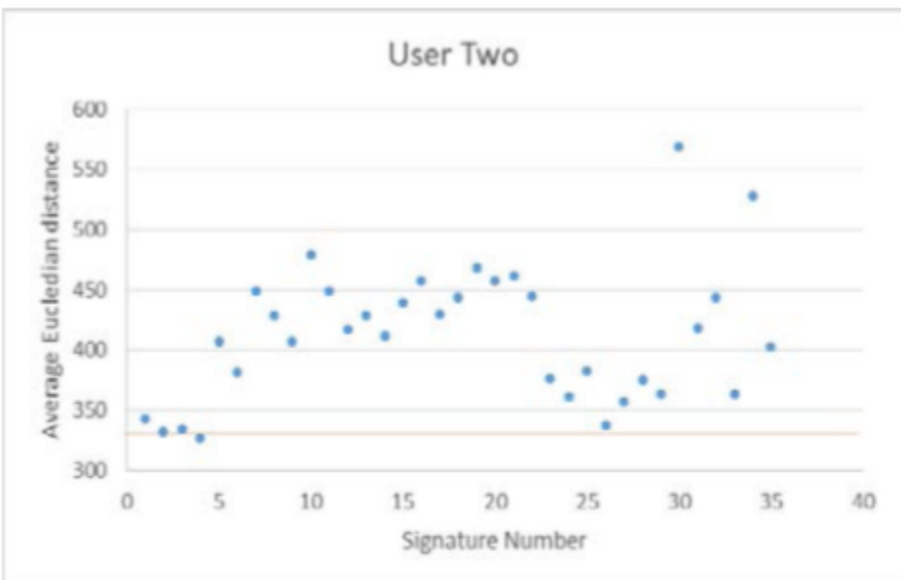

Fig. 8.2. Genuine-Genuine vs Genuine-Forged signatures for user two.

The same test is applied on the second dataset, but is applied by comparing between the first two genuine signatures and between the first genuine signature and another 3 forged signatures, the results are 100% verification accuracy of the forged signatures.

8.2 Parametric investigation of the model

A parametric study is applied in this work by changing threshold value in SURF detector. SURF detector depends on the Hessian matrix to find all interest points in a particular image. SURF divides the signature image into using second order Gaussian kernel and computes these kernels with box filter. The main function in EmguCV library is to detect interest points using SURF with Hessian threshold value. Experimental results show that best value for hessian Threshold could be from 300 to 500. The SURF detector considers those features in the signature image whose hessian is larger than a specified hessian threshold. Therefore, as high specified threshold value, as less key points in the image will be taken by detector but with more accuracy. A low specified threshold, high key point will be taken. When the Hessian threshold is 500, key points are 329 and when it is 100, key points are 1004. 1004 key points means many unnecessary key points is extracted from the feature , many calculation will be done which will increase the computational time of the algorithm and feature extracting will be not accurate. Therefore, after testing multiple signatures with different hessian threshold values best value for hessian threshold could be from 300 to 500. The chart below in figure 5 shows the relation between hessian threshold value with the accuracy and the number of the detected points. Therefore, the relation of hessian threshold value and number of interest point is inversely proportional.as shown in fig.4.3, higher hessian threshold value will result in less key points and lower hessian threshold will result more key points.

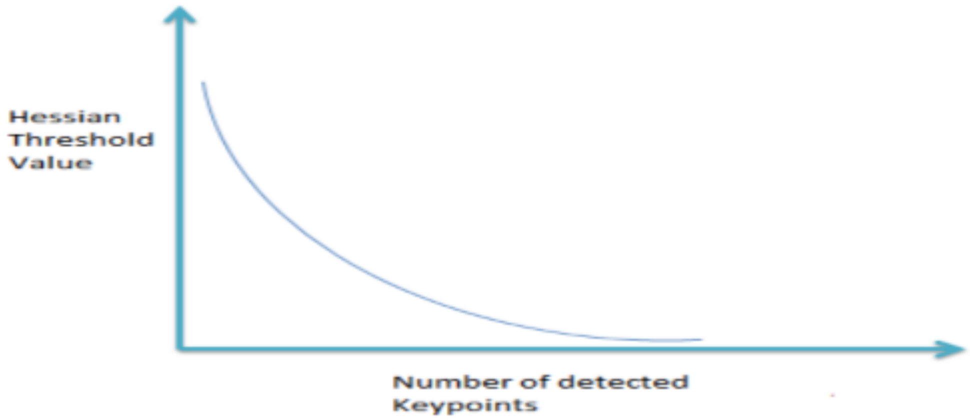

Fig.8.2. Relation between hessian threshold value and Number of interest points

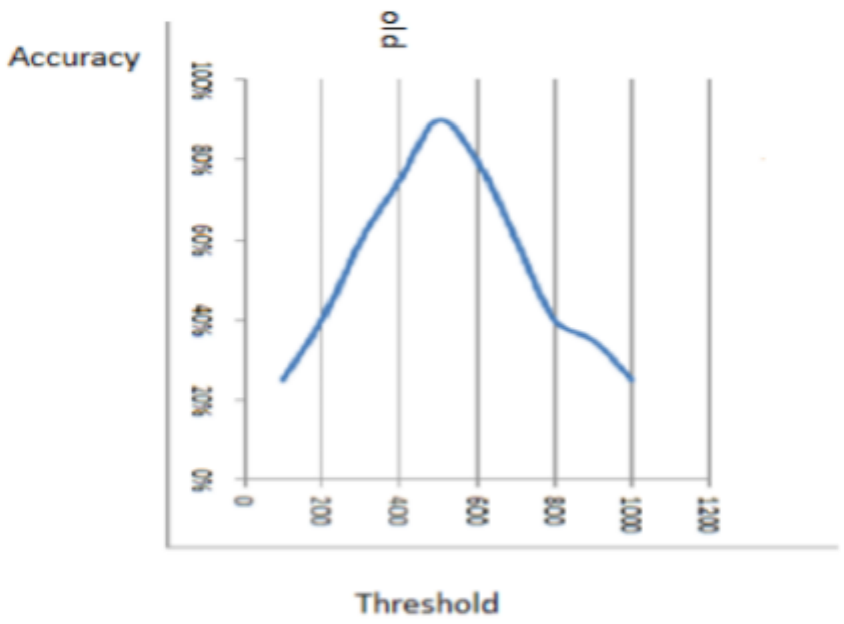

Fig.8.4. Relation between hessian threshold value and Accuracy of SURF detector.

As shown in fig.4.4, after testing multiple signatures with different hessian threshold value shows that the best accuracy of the software is when hessian threshold value between 300 and 500. As shown in the figure 5 above, higher hessian threshold value high accuracy and lower threshold value low accuracy until 500 after hessian threshold; value bigger than 500 , gives less detected points in the signature image which will make accuracy of the software less so the best value of hessian threshold is 500.

CHAPTER 9
CONCLUSION

Although the existence of an automatic signature verification tool is necessary, it is not yet applied in most of the financial institutions. The reason is that most of the currently available tools work with a highest accuracy of ca. 80%, which makes them not reliable in the verification task. For many years, researchers are trying to develop more robust signature verification tools using the advances in image processing algorithms. The main objective of this work is to offer an economically and efficient offline handwritten signature verification system, in order to achieve the objective multiple methods have been reviewed and surf features algorithm is used in this paper as strong image descriptor. Databases of signatures were collected and saved containing known writer's signatures. The proposed model was successfully verified signatures of users with a lowest accuracy of 85%, indicating its promising implementation and making a room for more improvements to be researched and investigated. The future work of the current study is to enhance the feature extraction step of the algorithm by adopting features related to cross correlation, and signature energy and skewness. Finally, an automatic feature extraction tool may be developed to predict the relevant features, which define each signature and reduce the verification effort.

CHAPTER 10

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