Multimodal Personal Authentication Using Gaussian Mixture Model and Support Vector Machine

Major Project Report submitted in partial fulfillment of the

Requirements for the award of degree of

Master of Technology

In

Information Systems

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New Delhi, 2011-13

CERTIFICATE

This is to certify that **Ms. Prerana Mukherjee (2K11/ISY/17)** has carried out the major project titled **"Multimodal Personal Authentication Using Gaussian Mixture Model and Support Vector Machine"** as a partial requirement for the award of Master of Technology degree in Information Systems by Delhi Technological University.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session **2011-2013**.

The matter contained in this report has not been submitted elsewhere for the award of any other degree.

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ACKNOWLEDGEMENT

I express my gratitude to my major project guide **Sh. Anil Singh Parihar**, **Asst. Professor**, **Dept. of IT,** Delhi Technological University, for the valuable support and guidance he provided in making this project. It is my pleasure to record my sincere thanks to my respected guide for his constructive criticism and insight without which the project would not have shaped as it has.

I would like to thank **Prof. O.P. Verma, HOD, Dept. of IT,** Delhi Technological University, for his useful insights and guidance towards the project. His suggestion and advice proved very valuable throughout. I humbly extend my words of gratitude to other faculty members of this department for providing their valuable help and time whenever it was required. I am thankful to all teaching or non-teaching staff of DTU and my fellows, who have helped me in the completion of this thesis report.

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ABSTRACT

In this work, different approaches like Gaussian Mixture Models (GMM) and Support Vector Machine (SVM) have been investigated for multimodal biometric authentication. There are various schemes for multimodal fusion like normalization techniques, classifier based approaches and density evaluation approaches. Finite mixture models like GMM have been used for multimodal biometric systems and which produces significantly good results on multimodal databases. Multimodal databases can be constituted of multiple instances of same biometric trait or can be obtained from various matching algorithms which determine the scores of genuine and imposter classes. The experiments have been performed on palmprint, knuckleprint and iris databases. Different feature extraction techniques like Gabor-Scale Invariant Feature Transform (SIFT), Gabor-Harris and Gabor-HOG has been used for feature extraction in palmprint and knuckleprint databases. These techniques work significantly well for both constrained(IITD) and unconstrained(PolyU) databases which are used in the work and produce efficient results for performance measures as compared to the prior techniques like line based approaches, texture based and appearance based approaches. GMM has been used for classification from the scores generated by these feature extraction techniques. The parameters evaluation for the GMM technique has been evaluated using Expectation-Maximization (EM) algorithm. Maximum Likelihood Estimation (MLE) further improvises the results of GMM. SVM which is active learning methods also results in good results for palm and knuckle database and gives optimal performance. The results show that these techniques are quite robust for multimodal authentication schemes.

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INTRODUCTION

1.1 Preview

Biometric authentication basically comprises of two aspects i.e. biometric verification and identification. In Biometric verification the template of an individual is checked with the same template already stored in the database in order to verify that the individual is the person who he claims to be using his/her biometric traits which includes physical (e.g., fingerprint, iris) or behavioral (e.g., signature) or chemical (e.g. composition of compounds in human sweat) characteristics or traits whereas in identification mode the given template is required to be matched with all the stored templates in the database in order to authenticate that the individual belongs to the same set of users in the database. The prior techniques of personal authentication requires the pin number or the password to be remembered which is quite cumbersome as in the case of ID cards (tokens) and also more susceptible to attacks anyone could steal them and use it by impersonating ones identity. As a result nowadays, biometric systems are being deployed in all the areas of high security domain interests and to reduce financial fraudulence in the form of credit card or smart card loss. Numerous biometric traits are being used for real-time recognition purposes, the most popular being fingerprint, vein, palmprint, face and iris [23, 24]. However, there exists other biometric systems as well that are based on retinal scan, voice, gait, keystroke pattern based and signature based. A biometric system typically comprises of some modules namely the acquisition module which obtains the biometric modality of the individual followed by a feature extraction system which employs some technique for extracting the features which are considered to be unique and distinct for each individual which are then matched using a matching system which uses a matching strategy based on distance or classification scheme to identify the genuine and imposter users. Sometimes multiple biometric traits are considered over a single biometric trait as it becomes more secure and difficult for the forger to attack which automatically results in less imposter attacks. In addition to this, failure to enroll situations can also be minimized in multimodal biometric systems [22]. Also, physically challenged people may use multimodal biometric systems for authentication if they are unable to register using a particular biometric trait.

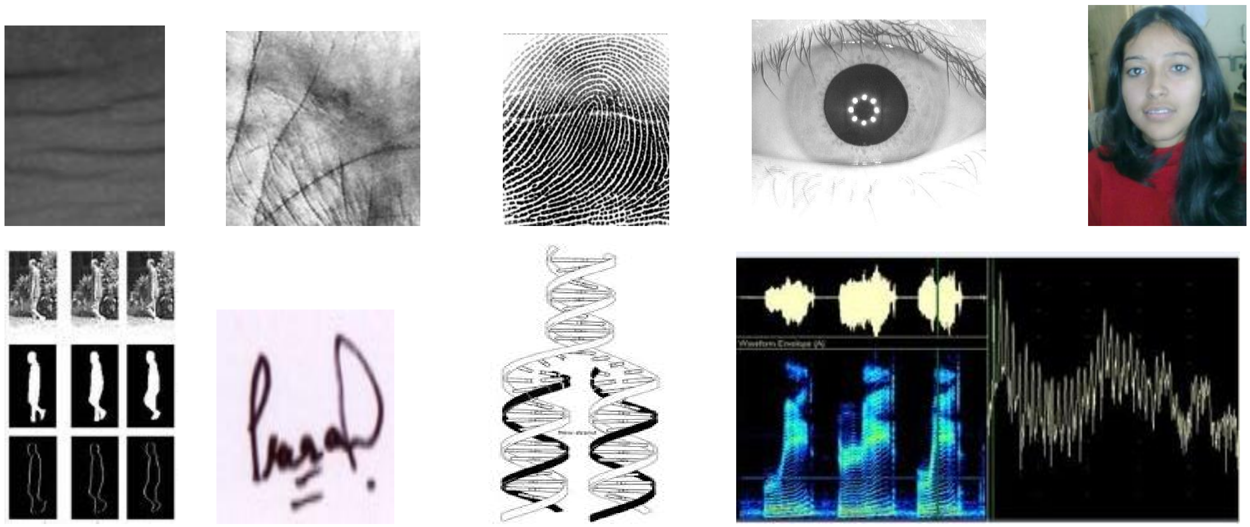


Figure 1.1: Different Biometric Traits a) Knuckle print b) Palm Print c) Fingerprint d) Iris Structure d) Face Biometric e) Gait pattern f) Signature Pattern g) DNA Pattern h) Voice Pattern

Biometric authentication suffers from several challenges, namely quality checking parameters, live-detection check, acquisition, user acceptance and convenience, description of features which includes proper detection and matching [12, 17]. Every biometric modality has its own pros and cons [12]. Iris acquisition poses difficulty as it has a small area which is tough to acquire at once as the user has to adjust the focus in a right dimension to complete the acquisition successfully. It is also not cost effective as the iris acquisition systems are quite expensive and difficult to deploy. Although iris is considered to be a stable and highly accurate biometric trait as it does not degenerate with the age and environmental factors and remains the same lifetime and has less false acceptance rates. Face recognition systems are considered as the most prevalent technique for authentication due to ease of acquisition. It finds an important application in computer vision domain to identify the faces in occluded environment and cluttered backgrounds. However it also has certain problems associated with it like it is difficult to identify the faces of in disguise due to the use of false beards and moustaches and other accessories like spectacles and face masks which hides the face and makes it nearly impossible to authenticate the identity of a person. Also face recognition is not useful for authentication in case of identical twins. In case of pose and expression variations it is not convenient to detect the identity of a person efficiently. 3D face recognition involves the use of highly sophisticated and expensive acquisition devices. Among the various biometric techniques used for authentication, hand based biometrics is well established trait, with some advantages over the already prevalent competitor techniques. It is so, because of the textural details which can be extracted from hand based features for authentication is high and the human hand data acquisition is convenient and user-friendly. Also, it is less exposed to anatomic variations and environmental changes. The acquisition done on hand based biometrics modalities have the most high recognition rates which are mostly done by contact device having pegs [5]. Hand-based biometrics has been used in personal identification by using fingerprint [23], palmprint [5], hand geometry [13], 3-D finger geometry [14], hand vein [15,16] and knuckles [6-9]. The most widely and reliable modality considered out of all of these traits is fingerprint which gives highly accurate results. Although, NIST has investigated that ~2% of the population does not have accessible fingerprints which are not quite useful thus fingerprint identification is useless for such people [1]. Also dryness or dirt that gets accumulated on fingers can result in less reliable results. In addition to this, people generally have a tendency to touch the acquisition devices during authentication and thus their fingerprints may get left unconsciously which may increase the possibility of imposter attacks during the result investigation. Knuckles are another promising feature for personal authentication nowadays [6-9] since they are convenient to acquire and can be captured using ordinary digital cameras. In knuckle authentication the only concern is that we have to take into consideration the impression of all the knuckles of both the hands of the user which results in an increase in the number of samples for each user which need to be stored in the database, thus maintenance of such huge database becomes quite cumbersome. But in case of palm print, the surface area is large so it carries better and useful information which makes it more suitable to be used as a biometric modality [10, 11]. The capture devices for palmprint authentication are also cost effective and the memory required for storage is not much in case of low resolution images of the palm. So, palmprint serves as the better alternative from the hand based modalities [21].

1.2 Why Multimodal Biometrics Schemes are used for consideration?

Unimodal biometrics includes the establishment of identification of an individual based on a particular biometric trait which could be the iris pattern, fingerprints, voice, hand gesture, facial features, ear, DNA sample, palmprint, gait pattern or a signature of the individual. Since it is based on a single root of information it becomes very easy to forge it and make a false claim for identification. Thus it suffers from some problems as follows [12]:

1. Sensor Noise: During the acquisition of a biometric trait noise may get embedded along with the data resulting in false matches by the matching module as it will match the noisy data with the existing template present in the database. Sometimes the sensors also get dirty due to dust present on the surface of the sensor or the impressions of fingerprint or palmprint which is left behind as a large number of users may come to register the biometric trait. In voice recognition the user may suffer from cold and the sensor cannot recognize the voice pattern. Poor illumination conditions and wrong focus of the camera can also result in noisy data as the face or the iris captured in such conditions may not be foolproof for authentication purposes. Thus in order to maintain full fledged accuracy in the system the acquisition devices should be properly maintained and kept in dirt free environment.

2. Lack of distinctiveness: each biometric trait is considered to be distinct and possessed by all individuals thus making it universal in nature. Although it may also suffer from some intra class variations. This variation may occur due to the template data which may not be getting accurately enrolled due to the frequent change of sensors or due to user interaction with the sensor like in case of face recognition if a person gives more profiles and pose variations the matching module may not be able to classify them into one class irrespective of the samples belonging to the same user. In case of identical twins the face biometrics is not relevant. The manual workers who work in the fields may have creases on their fingerprint due to which their finger samples do not give accurate results when matched. As investigated by NIST, ~2% of the population does not have useful and accessible fingerprints thus fingerprint identification is useless for such people. Thus the universality of the biometric trait is lost in such cases and it is highly difficult to discriminate the genuine and imposter users. These types of problems cause an increase in the Failure To Enroll (FTE), Failure To Capture (FTC) error rates.

3. Spoofing attacks: It is easier to forge a single biometric modality in comparison to create false samples for multimodal biometric systems. Fake fingerprints and hand geometry from fake hands are most common spoofs in behavioral biometric traits. Signature can be easily copied by professionals and voice modulation can be done to get access to high security areas. Gummy finger are nowadays easy to construct which involves the use of a

mold to get the impression of an individual's fingerprint in which a liquid is then poured and allowed to settle down creating an artificial finger for an illegitimate user to circumvent a system.

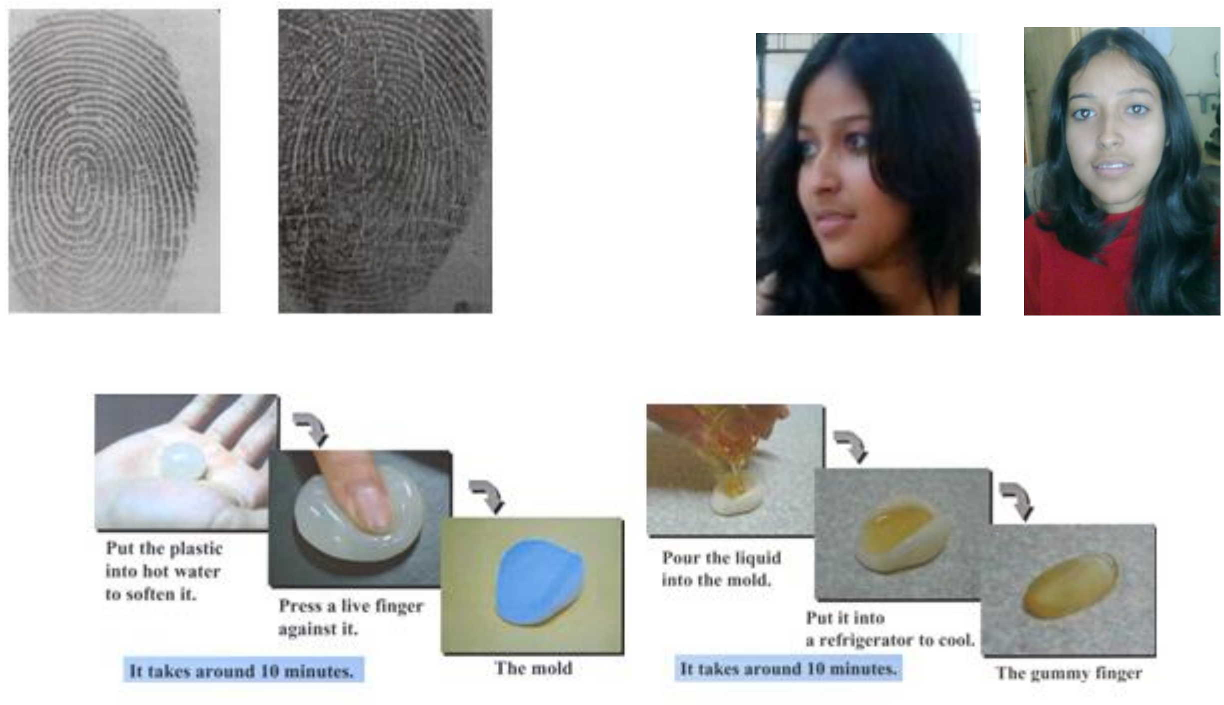


Figure 1.2: Limitations of Unimodal Biometrics a) Noise in Fingerprint of a Manual Labor due to creases b) Different face profiles difficult to identify c) Spoof Attacks of Fingerprint[28]

Thus Multimodal biometrics like multiple fingerprints, face and palmprint etc result in high performance in terms of high recognition rates as they are multiple and independent from each other and also overcomes the drawbacks of spoofing in case of unimodal systems. Multimodal systems also provide a fast and efficient search from a large database thus saving time and efforts. Initially a less expensive and less accurate biometric modality can be used to train the system and finally when the learning is done it can be used for classification which can be done using complicated and relatively more accurate biometric traits to get correct results from matching. However the multimodal systems also suffer from certain limitations like the user has to give multiple cues of biometrics which are then fused using an efficient technique to do the matching which may be of little inconvenience for the user as it is time consuming and unmanageable task to create a large storage for these multiple traits which further involves complex computations to do the matching. The system accuracy may also get questionable with respect to unimodal systems if the fusion strategy for multiple biometrics is not efficient enough to distinguish the traits of different individuals. However, on the whole multimodal biometric systems are far more advantageous over unimodal systems to overlook these disadvantages. [28]

The integration of information in multimodal biometric systems depends on the way in which the data obtained from various sensors is fused i.e. the fusion of data can occur at 4 stages namely:

i. Fusion at sensor level

ii. Fusion at feature level

iii. Fusion at matching level

iv. Fusion at decision level

It may also differ in the architecture of the multimodal biometric systems as there are 3 operational modes viz. serial mode, parallel mode and hierarchical mode. The architecture is defined by the manner in which the different biometric modalities are obtained from their respective sources and finally how they are integrated to get the desired results. In serial mode the biometric modalities are processed in serial order. The output of first biometric trait is narrowed down first then we use the next biometric trait e.g. if we are using the combination of face and palmprint to authenticate the user, firstly the results from face recognition module would be done to get top face matches and then the palmprint template would be matched with only those persons whose faces have been identified in the previous stage of face recognition. The parallel mode uses the simultaneous use of different biometric modalities to establish the identity of the user e.g. there is an iris scanner which is extracting and localizing the iris patterns simultaneously the user can give his palmprint on the other scanner. In hierarchical or hybrid mode various classifiers are used in treelike structures to give the decision results. It includes the advantages of both the serial as well as the parallel mode.

In serial mode there is no propagation delay as soon as the results of on biometric trait is not obtained the next biometrics is analyzed. It also results in fast and efficient searches from large databases as if the results are satisfactory from one biometric we can choose which other biometric combination will give the best possible results thereby reducing the time in searching process. Thus a serial mode is generally preferred due to its convenience to use but depending on the requirement of the application the operating modes may differ. The advantage of parallel mode is that it can even work in the absence of a particular biometric trait and gives higher accuracy rates and reduction in error rates as it authenticates on the basis of multiple cues simultaneously. The choice of the operating mode entirely depends on the domain of interest. If multimodal biometric authentication is required in less sensitive areas like shopping marts and offices then cascaded or serial mode can serve the purpose but in areas of high security needs like defense and military services parallel mode would be more efficient to use. The hierarchical mode works in a robust environment and can handle noisy and missing biometric data.

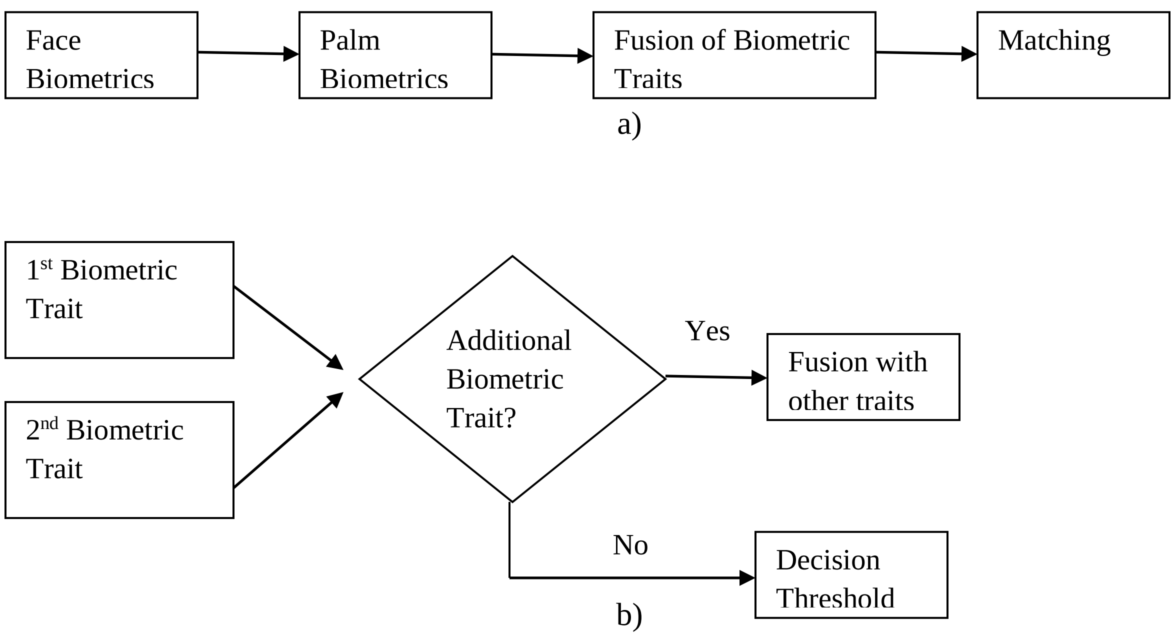


Figure 1.3: Operational Modes in Multimodal biometric Systems a) Serial Mode b) Parallel Mode

Based on the source of information also the multimodal biometric systems can be classified. The data can be collected from multiple sensors using the same biometric trait like the fingerprint information is obtained from the optical sensor and a capacitive sensor. It could be a combination of different biometric traits like face with hand geometry and face with iris or it could be multiple instances of the same biometrics e.g. the fingerprints of two or more fingers and both the knuckleprints left hand index finger and right hand index finger. There could be difference in the pose snapshots of the face or multiple impressions of the same finger. Multiple representations or matching algorithms could also provide variations e.g. the matching scores obtained from textural features and matching scores obtained from minutiae features.

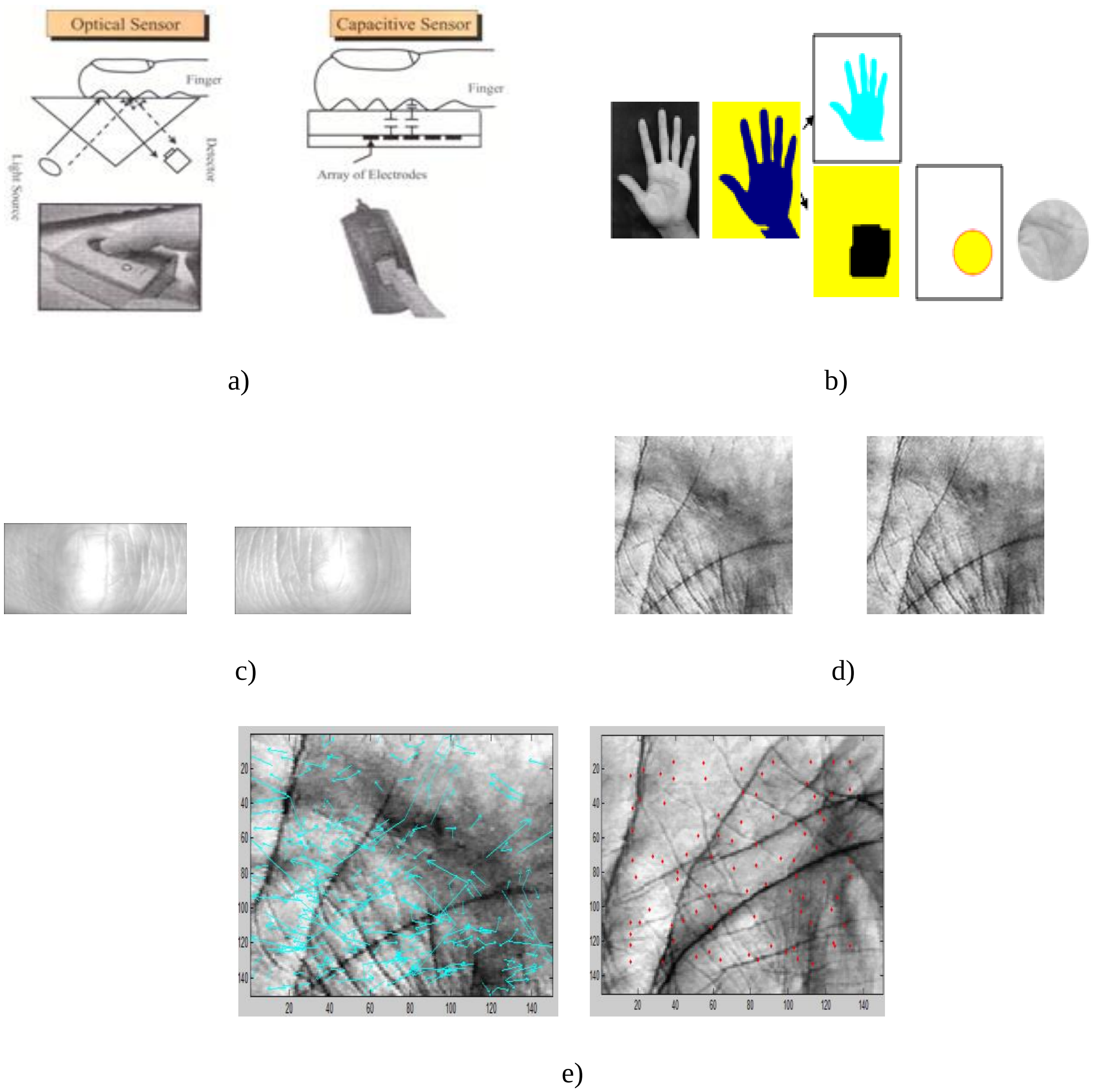


Figure 1.4: Multimodal Biometric Systems a) Multiple Sensors b) Multiple Biometrics (Palmprint+Hand Geometry) c)Multiple Units of Same Biometric (knuckle print of left index finger and right index finger) d)Multiple snapshots of same biometric(left hand palmprint) e)Multiple representations of same biometric (matching scores by SIFT and Harris algorithms)

1.2.1 The Fusion Strategies

1. Fusion at sensor level: The same biometric trait can be obtained from different scanners or sensors to create a variance in the data obtained. The fingerprint can be obtained using a capacitive sensor and an optical sensor which are compatible in properties to each other. Multiple cues or instances of a single biometrics using a single sensor can also be used for fusion at sensor level. The data collected from different cameras with varying illumination and resolution properties cannot be used for fusion as it will result in inconsistent data resulting in false matches.

2. Fusion at feature level: It involves the fusion at representation level. The feature vectors from different biometric traits are firstly scaled in the same range which is then concatenated. The decision from the decision module is finally taken from the combined feature vector.

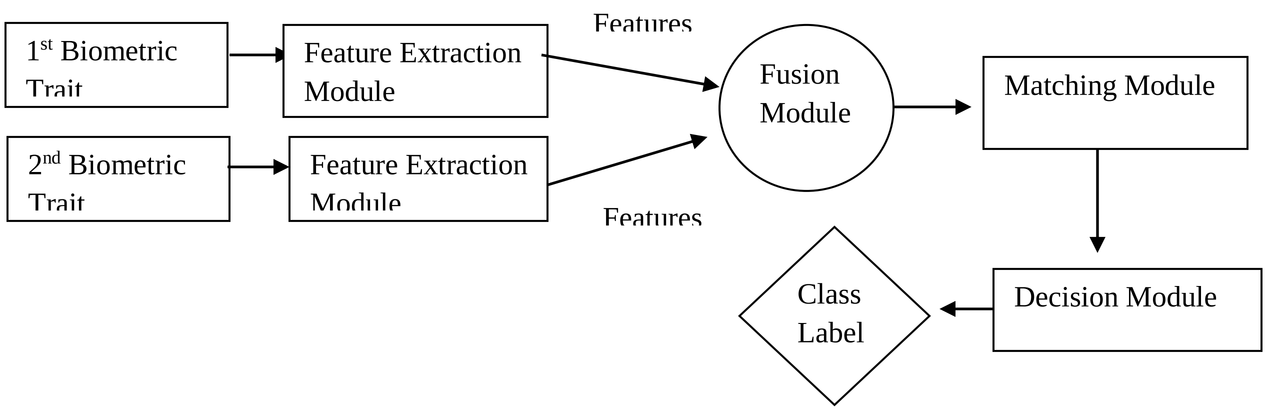


Figure 1.5: Block Diagram for Feature Level Fusion

e.g. The feature vector from palmprint / face is obtained of size 1xn and 1xm is obtained f_{Palm} / f_{Face}, which is then normalized as follows

$$\tilde{f}_{Palm} / \tilde{f}_{Face}, \ (1 \times (M+N)) \tag{1.1}$$

and a combined feature vector is formed.

$$x_q = \left[\tilde{f}_{Palm} \ \ \tilde{f}_{Face} \right] \tag{1.2}$$

and a similarity score is obtained using x_q

$$\eta_{match} = \frac{\sum x_q x_c}{\sqrt{\sum x_q^2 \sum x_c^2}} \quad \text{or} \quad \eta_{match} = \|x_q - x_c\| \qquad (1.3)$$

and based on the decision threshold the classification is done.

3. Fusion at matching score level: Similarity scores from feature vectors of each biometric is first obtained. Decision thresholds or biometric weights can be assigned to each biometric trait to get the results.

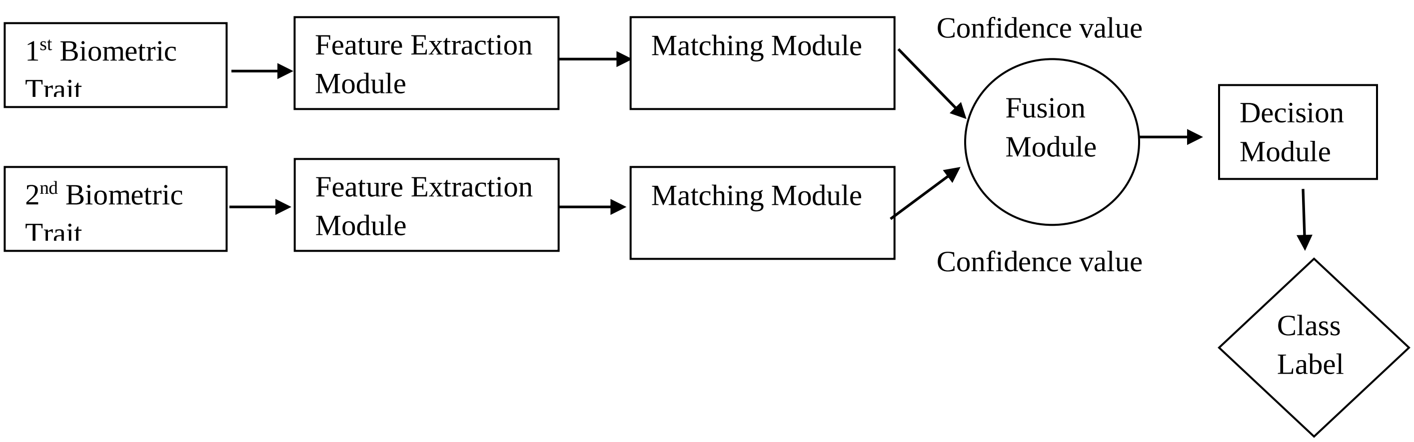


Figure 1.6: Block Diagram for Matching Score Level Fusion

e.g. Given $\{n_1, n_2\}$ assign user U to one of the two classes $\{c_1|c_2\}$ where c_1-genuine and c_2-imposter. Assign $U \rightarrow c_x$ if $P(c_x| n_1, n_2)=\max\{P(c1| n_1, n_2),P(c2| n_1, n_2)\}$ where $P(c1| n_1, n_2)$ and $P(c2| n_1, n_2)$ are posteriori probability for genuine and imposter class for given $\{ n_1, n_2\}$respectively.

Assuming statistical independence, estimation of $P(n_1, n_2| c_x)$ can be estimated using simple rules:

i. Sum Rule: $P'(c_x | n_1, n_2)=0.5 \{P(c_x | n_1)+ P(c_x | n_2)\}$ (1.4)

ii. Max Rule: $P'(c_x | n_1, n_2)=\max \{P(c_x | n_1), P(c_x | n_2)\}$ (1.5)

iii. Product Rule: $P'(c_x | n_1, n_2)=\{P(c_x | n_1)* P(c_x | n_2)\}$ (1.6)

iv. Weighted Sum Rule: $P'(c_x | n_1, n_2)=\{W1P(c_x | n_1)+ W2\, P(c_x | n_2)\}$ (1.7)

and W1+W2=1

where the weights could be estimated using performance indices e.g. (FAR + FRR)

$$W_1 = \frac{1-(FAR_1 + FRR_1)}{2-(FAR_2 + FRR_2 + FAR_1 + FRR_1)} \quad (1.8)$$

4. Fusion at decision level: Decision for each biometric modality is taken followed by combined decision which is based on majority voting or user specific weights.

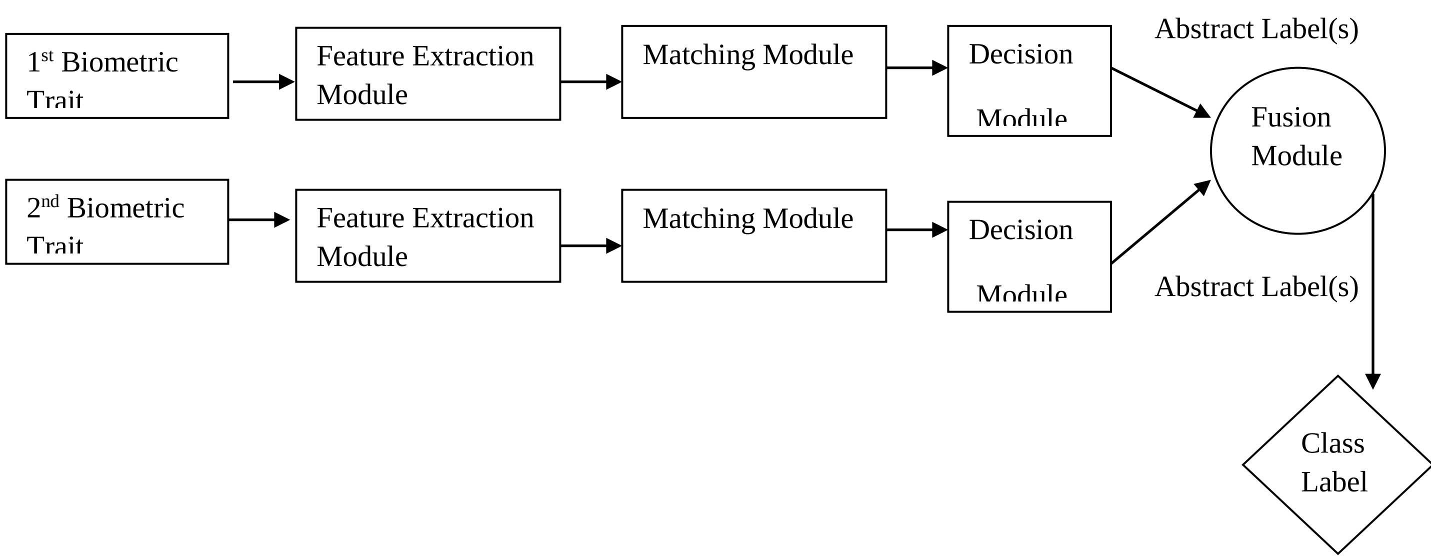


Figure 1.7: Block Diagram for Decision Level Fusion

Score Normalization can be done using the following rules:

i. Min-Max

ii. Scaling

iii. Z-score

iv. Median: Formula is as under:

$$s' = \frac{s - medians}{MAD} \tag{1.9}$$

$$MAD = median(s - medians) \tag{1.10}$$

v. Double Sigmoid: Formula is as under:

$$s' = \frac{1}{1 + exp\left\{-2\left(\frac{s-t}{\tau}\right)\right\}} \tag{1.11}$$

vi. Tanh: Formula is as under:

$$s' = 0.05\left[\tanh\left\{0.01\,\frac{s-\mu}{\sigma}\right\} + 1\right] \tag{1.12}$$

Most efficient among these normalization techniques is Min-Max, Z-score, Tanh rule and most robust being Median, Double-Sigmoid, Tanh rule.

1.3 Why contactless plamprint?

Numerous techniques and research work has been proposed in the field of palmprint authentication since the last decade by various researchers. Most of the work that has been done is available in reference to the contact-based palmprint acquisition as per the literature work. So there is a lot of emphasis given to the real life scenario based acquisition in terms of contact-based (constrained) palmprint authentication which has aroused research interest towards constrained free natural contact-less palmprint authentication. Touchless acquisition of palmprint is convenient from user's point of view and does not suffer from any translational or scale variations as the hand can be acquired from a distance as well.

Palmprint has several advantages over various hand based biometric modalities as follows:

1) The palm has a larger surface area so more number of features can be extracted as compared to fingerprint and knuckle print. So, they carry more information which improves personal identification and thus makes it a highly accurate biometric modality [5].

2) Palmprint capture devices are much low in cost [5].

3) Since the palmprint can also be extracted from low resolution images the memory requirement for storage of these images is reduced [5].

4) In fingerprint, factors like dryness, dirt or grease can result in increase in imposter attacks and wrong results while such problems do not occur in palmprint image acquisition.

5) Palmprint contains more unique and descriptive features than 3-D hand geometry and thus a better biometric modality.

Preprocessing includes the steps which are used on hand image to extract palmprint.

Initially apply a low pass filter like Gaussian filter to the original image followed by the following steps.

I) Binarization
II) Hand Boundary Tracing
III) Region of Interest extraction.

i. Binarization

Based on a typical threshold value (threshold obtained from Otsu's method) the binarization of the image is done A threshold value is selected using otsu's metod which is used to binarize the image.

BI (i.j)=0 if I (i, j) ≤ Global_Threshold

1 otherwise

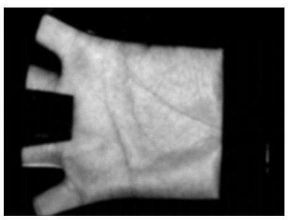
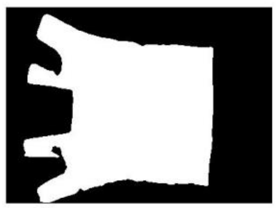
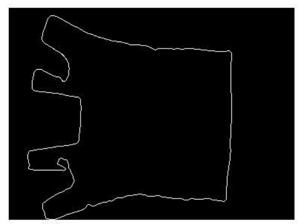
where value of black pixel is 0 and white pixel is 1.

ii. Hand Boundary Tracing

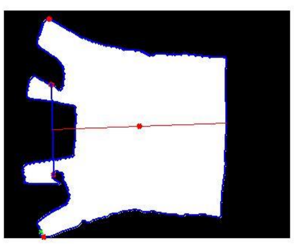
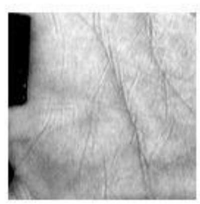
Once the binarized image is obtained the border of the hand is traced with reference to a starting point which acts as the reference point and the relative Euclidean distances are computed for each point lying on the contour region.

iii. Region of Interest(roi) extraction

The relative distances of every border point with the reference point is stored and a plot is drawn which gives the local minimas as the valley points P1 and P2 which can be joined and a perpendicular is drawn passing through the center of the hand till the reference point. The roi of required dimensions i.e. 150x150 is then extracted.

a) b) c)

d) e)

Figure 1.9: ROI extraction for PolyU database a)Palm image of the user b)binarised image of the palm c) boundary of the palm d) contour with valley points of the palm e) Extracted ROI image

After the ROI is extracted, the following steps are done for palmprint verification:

i. Detection of features: Interesting features are extracted from the preprocessed image i.e. ROI. Detectors used for extracting these features are SIFT, HARRIS, AND HOG.

   Scale invariant feature transform (SIFT) is an approach for detecting and extracting local feature descriptor which are invariant to scale and rotation. HARRIS is an approach to detect and extracting corners from the palmprint image which are invariant to scale and illumination. Histogram of oriented gradient (HOG) is feature descriptor that represents occurrences of gradient orientation in localized portions of an image.

ii. Description: Descriptor is anything which describes the properties of an image like color, orientation, texture, pixel intensity, edges etc. In palmprint, unique properties can be texture, orientation , scale etc. Descriptor with edge orientation information (sift, hog) in our work have been used.

iii. Matching: Local feature descriptors of palmprint images are then matched using suitable similarity measure. In our work we have used cosine similarity for this purpose.

1.4 The Problem Statement

In the present research work, efforts are made to propose an efficient method for personal authentication of multimodal biometric traits using Gaussian Mixture Model and Support Vector Machines. Both these methods classify the input data into genuine and imposter sets. Gaussian Mixture Model is supervised technique which requires some predetermined parameters for classification which are estimated using EM (Expectation and Maximization) algorithm. The biometric traits which have been used are Palmprint, Knuckleprint and Iris codes. In EM algorithm the estimation of parameters is based on some latent variables which are associated with each input data which requires some initial set of some parameters. These parameters are fine tuned with every iteration in order to maximize the value of maximum likelihood. The algorithm is able to handle missing data. GMM is based on density based score fusion as it estimates the genuine and imposter match score densities. It is intractable to find the maximum likelihood value directly. EM algorithm handles this by solving the linear equation simultaneously. Either the maximum likelihood value is known and we proceed to find the correct estimate of parameters using the latent variables and input data set or using an initial estimate of parameters the maximum likelihood function is found. GMM is better than other density estimators like Kernel Density Estimator (KDE) as it is required to know the kernel bandwidth and computation of density at ends of continuous input data is difficult and GMM can give a correct estimate for genuine and imposter match scores. The multimodal biometric system constitutes scores obtained from different matchers or different traits. These scores are first fused using score level fusion techniques. GMM estimates the Gaussian densities for the matching scores which are classified into genuine and imposter distributions using an adaptive threshold value. GMM gives a consistently high performance for multimodal biometric data sets so is a useful technique for classification. MLE can further improvise the results when the likelihood estimates for the genuine and imposter score densities were found.

SVM (Support Vector Machines) are active learning technique which is a binary classification technique in which the input data set is classified into any of the two classes or groups based on the apriori known classification of the training data based on a certain decision rule set. SVMs do a matching of the training data into high dimension feature set implicitly. The input data is segregated into two classes based on the hyperplanes or decision surfaces that are constructed and the distance is maximized between hyperplanes and points lying near them which are known as support vectors. Thus these decision surfaces help in the classification. SVM has been used in the experimentation to get the performance measures on different biometric traits like palmprint and knuckleprint. For every 5 samples corresponding to each user were divided into 2 sets 2 samples and 3 samples. Out of the 3 sample set 1 was taken as training data and 2 as test data. The training sample was trained using a label in SVM which treats the not a number and empty strings as missing data and gives a svm structure element with the fields having support vectors, alpha, bias, kernel functions, kernel function arguments, group names, support vector index, scaling data. Kernel function could be linear which uses the dot product or quadratic kernel. For the experimentation Gaussian radial basis function takes default kernel with sigma 1 was used. The test samples were then classified using the svm structure element. The error rates were estimated for the palmprint and knuckleprint databases. Membership values have also been assigned to the training data which assigns some weights for different sample sets in the training data and the results after hard conditioning on the data has also been analyzed.

1.5 Databases Used

The first database is the PolyU palmprint database which is widely employed palmprint database. This database is a constrained database as user pegs are used to confine the hand movements which would restrict the scale variations and view change in the images. Due to the use of pegs it is not suitable in real life scenarios as the user has to restrict the hand movements and place the hands accordingly to get the correct imaging.

The second database is the IIT Delhi palmprint image database which consists of the left and right hand images which have been sampled from the people and students working in IIT Delhi. The database has been captured in a contact less sensor setup which is unconstrained and quite simple to use. The images have been acquired in inside the building in a constant illumination around which is fluorescent in nature around the lenses of the camera. The number of user samples is 235 and the images are stored in BMP (Bitmap) format. The users belong to the age group [12-57] years. Seven left hand images from each user, thus, a total of 1645 samples are acquired in different hand pose changes. Each user is provided with live feedback to give his/her hand in the imaging region. The images taken are numbered sequentially corresponding to each subject and given a unique identification number which is associated with it. The contact-less imaging gives higher image scale variations.

The iris database is from CASIA database and knuckle database is from PolyU and IITD database.

1.6 Prior Work and Motivation

Most of the researchers have shown keen interest in palmprint authentication but most of the work has been carried out on contact-based databases with prior techniques which are not ideally suited for contactless databases. Feature detectors like SIFT, Harris Corner, Hessian affine detector and HOG work extremely well in touchless authentication systems. These detectors can be based on detection of corner of the region or center of the region. The features extracted by these detectors can be used to classify the users into genuine and imposter classes using different classifiers.

Xuan *et al.* have compared the methods employed in finite mixture models like GMM and HMM and have showed that the EM algorithm employed in GMM is a special case of EM of HMM and that the EM algorithm for observation set in GMM is slower in comparison to the EM algorithm of symbols [26]. Reynolds *et al.* have introduced the use of GMM in speaker identification. The speaker identity in this can be modeled using the Gaussian components and is robust to the degradations in the communication of a telephone channel and have shown high identification accuracy [27]. Nandkumar *et al.* have worked on likelihood ratio test based authentication for biometric score fusion which can handle discrete values in the biometric scores and worked well for multiple matchers [28]. Hosseinzadeh *et al.* proposed a novel keystroke feature and did its comparative analysis with the features of GMM based system [29]. Wang *et al.* investigated the score level fusion using GMM on iris and palmprint features [30]. Raghavendra *et al.* worked on fused scores using GMM and Monte Carlo's method which achieves higher performance rates than the normal fusion methods [31]. Figueiredo *et al.* proposed an algorithm for multivariate data which is not sensitive to the initialization of parameters [32].

Kumra *et al.* have done palmprint feature extraction using LDA method and performance measures using SVM has been investigated [34]. Kumar *et al.* have reported comparative performance using Gabor and line based features using score level fusion on palmprint features [35]. Guo *et al.* have proposed a novel algorithm known as binary co-occurrence vector algorithm [36]. Hanmandlu *et al.* have proposed four methods for feature extraction which are matched using Euclidean distance, chi-square and svm methods [37][39]. Wand *et al.* have discussed multiple parallel SVM strategy [38].

GMM and SVM can be effective in multimodal biometric personal authentication and give significantly good results and it can be employed in contact-less database scores.

CHAPTER 2

Feature Extraction Techniques

2.1 Feature Extraction

Keypoint or Feature point detection is a vital step in biometric authentication and involves a lot of attention from research point of view. Every image consists of some particular features, points or key points that need to be extracted from the image. The input data which is acquired by sophisticated acquisition techniques is transformed into a reduced feature set known as the feature vector which provides a great deal of condensed information which is not usually available from the input data directly. The visual features comprise of domain specific features (e.g. fingerprints, human faces) or general features (viz. color, texture and shape). The features that are needed to be extracted are application dependent and once they are computed they can be used for analysis.

The shape features broadly gives the outline of any image which includes segmentation of the image followed by various morphological operations which gives the contour of the image. Object based features may include Euler number, perimeter, area of the center and the aspect ratio of the image which are computed using various mathematical calculations. Color features help in classification of objects based on the color bands.

In the feature space, the feature vector constitutes an n-dimensional feature set where each point corresponds to the value of each feature. The difference between any two set of feature vector can be estimated using various similarity measure like Euclidean distance, L-norm, cosine similarity. The similarity searching for matching can be done by performing operations on the normalized feature vectors. These have low computational overhead and improvise the results. The most popular and intuitive choice for similarity measure, the cosine function is considered for this work.

A number of prior techniques have been employed by various researchers but the existing approaches are not so promising for contact-less databases these images consist of variances like that of scale, rotation and translation. So, a need for such detectors is there which can deal with the images having variations and gives the best authentication results. The detectors explained below will address these variations. Here, the acquisition is considered to be done under constant fluorescent illumination circumstances. Interesting features are extracted from the pre-processed image i.e. ROI. Every image consists of some particular features, points or key points that need to be extracted from the image. The palm consists of principal lines, wrinkles (secondary lines) and epidermal ridges. The skin folds and creases serve as the distinct features in knuckle print.

The detectors which were used for feature extraction included SIFT, Harris corner detector and HOG. The matching strategy used for matching these features was cosine similarity.

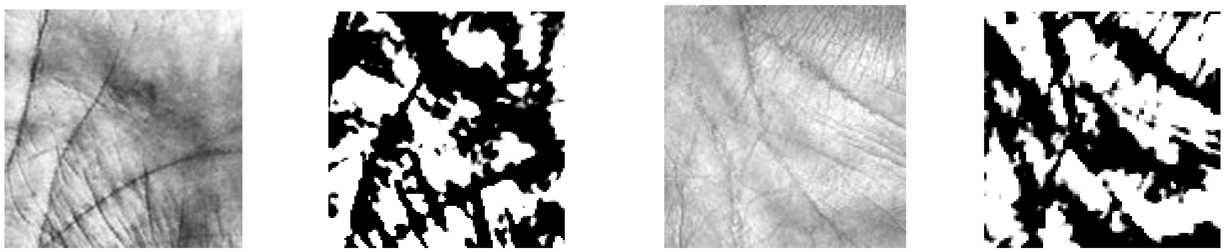
2.2 Feature Extraction Approaches for Palmprint and Knuckle Authentication

In the proposed approach, Gabor filter is being utilized to improve the features in palmprints and knuckleprints for both contact-based and contact-less databases. Harris feature detection technique makes use of the Gabor filter initially to enhance the textural features in which the corners are then detected and described using the SIFT descriptor at various scales. HOG which is a feature detector and descriptor both has also been used for the experimental work.

2.2.1 Scale Invariant Feature Transform

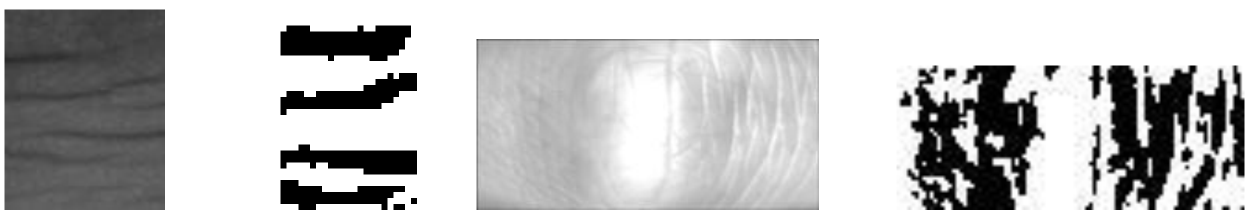
Scale-invariant feature transform (SIFT) is a powerful detector extensively used in the pattern recognition and computer vision fields. SIFT is a local feature descriptor used for detection of features which are invariant to scale and rotation. The pre-processed palm print and knuckleprint ROIs are used in SIFT feature extraction. In case of palmprint authentication, features consist of principal lines, wrinkles (secondary lines) and epidermal ridges and for knuckle print they are the crease lines. The principal lines are not sufficient to uniquely represent the individuality of a user’s palmprint because different people may have similar principal lines in their palmprints.

Gabor filter was used to enhance the textural features. The results have been shown in Figure 2.1 and 2.2.



a) b) c) d)

Figure 2.1: (a) ROI of the left palm print of a user (IITD database), (b) GROI of (a), (c) ROI of the left palm print of a user (PolyU database), (b) GROI of (c).



a) b) c) d)

Figure 2.2: (a) ROI of the left index knuckle print of a user (IITD database), (b) GROI of (a), (c) ROI of the left index knuckle print of a user (PolyU database), (b) GROI of (c).

These ROI's which are obtained are then used for feature extraction. The first step in SIFT detection is the detection of scale space extrema. A Gaussian blurred image is taken which is produced as a result of convolution of the ROI image with the Gaussian filter which is known as the scale space of the image. Difference of such Gaussian images is taken at various scales. Each pixel is compared with its 26 neighbours that include the 9 pixels on the scales above and below the DOG images and the 8 surrounding pixels of the current scale to give the local maxima and minima of this scale space function. The keypoint localization is done by removing low contrast and those which are located on the edges as they are susceptible to noise. For each image sample, at this scale, the gradient magnitude and orientation are computed by the given formula:

$$F(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{2.1}$$

$$\text{magnitude}(x,y) = \sqrt{\big(F(x+1,y) - F(x-1,y)\big)^2 + \big(F(x,y+1) - F(x,y-1)\big)^2} \tag{2.2}$$

$$\text{orientation}(x,y)=\tan^{-1}\left(\frac{F(x,y+1)-F(x,y-1)}{F(x+1,y)-F(x-1,y)}\right) \qquad (2.3)$$

Orientation assignment is then done using orientation histograms. An orientation histogram is obtained with 36 bins over a range of orientations (360 degree range). Each sample is weighed by the gradient magnitude and by a Gaussian window scaled to 1.5 times the scale of each feature point. The peaks in the orientation histogram amount to dominant directions of local gradients.

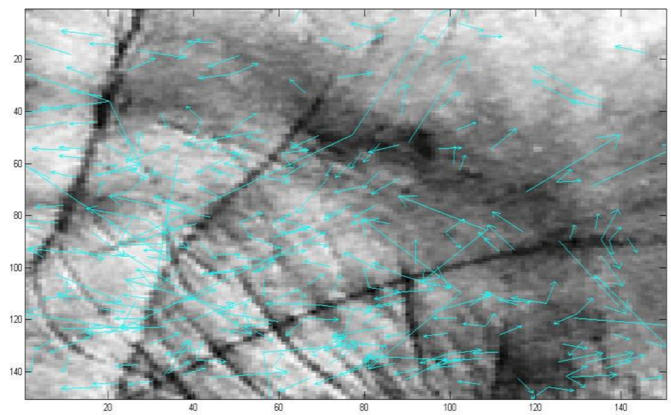


Figure 2.3: SIFT keypoints detected in a palmprint ROI

Any local peak that is within 80% of the highest peak is used to create a key point with that orientation. For multiple peaks associated to a keypoint multiple keypoints are created with different orientations but same scale. 15% of such points are only assigned. Detailed description can be found in Lowe [18]. Figure 2.3 shows sample palm print SIFT extraction results.

2.2.2 Harris Corner Detector

Corners are the points which have significant change in the intensity value in all the directions. In Harris corner detector the sum squared difference is defined between an image patch and another patch which is shifted by an offset value (x, y) known as the auto correlation function given by:

$$S(x,y)=\sum_u \sum_v w(u,v)\,(I(u,v)-I(u-x,v-y))^2 \qquad (2.4)$$

Where w(u, v) is a Gaussian window.

Using Taylor's series expansion first order approximation i.e. given by:

$$f(x+u, y+v) \approx f(x,y)+uf_x(x,y)+vf_y(x,y) \tag{2.5}$$

Eqn. 2.4 can be rewritten as:

$$S(x,y) = [u\ v]\left(\sum \begin{bmatrix} Ix2 & IxIy \\ IxIy & Iy2 \end{bmatrix}\right)\begin{bmatrix} u \\ v \end{bmatrix} \tag{2.6}$$

$$M(x,y)= \left(\sum w(x,y) \begin{bmatrix} Ix2 & IxIy \\ IxIy & Iy2 \end{bmatrix}\right) \tag{2.7}$$

The Eigen values are computed for matrix M. Corner response measure is then computed which is quite large in case of corners.

$$R=\text{determinant } (M)-k*\text{trace } (M)^2 \tag{2.8}$$

where k≈[0.04-0.06].

After thresholding only local maxima of R is taken as the corner feature.

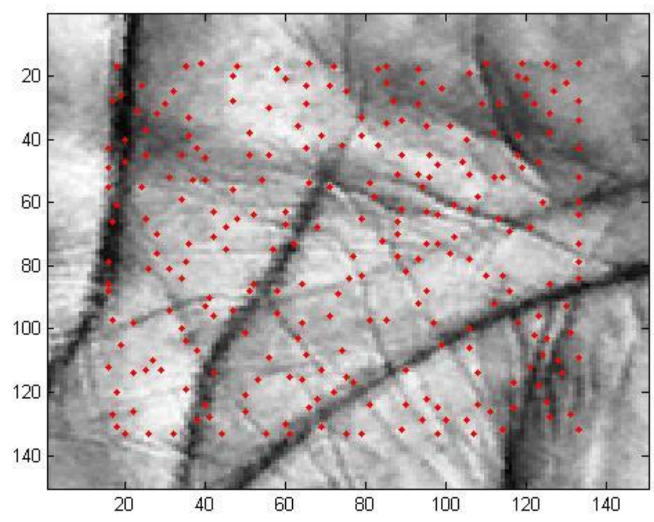


Figure 2.4: Harris Corners detected in a palmprint ROI

2.2.3 HOG- Histogram of Gradients

The different variants of HOG descriptor may include Rectangular HOG (R-HOG) or the Circular HOG (C-HOG) where the central cell gets divided into angled sectors. The gradient orientation in the local cell of an image is indicated by their count occurrences in a set of local histograms which gives the HOG descriptor. This image is divided into small spatial regions or cells which contain histogram of the gradients which are contrast normalized to give the results in the descriptor, thus giving the feature vector.

2.3 Feature Extraction Approaches for Iris Authentication

The combined layers of the epithelial cells which are pigmented, thin muscular tissues responsible for the control of the pupil movements and the stromal layer composed of blood vessels and joining tissues collectively result in the formation of iris patterns. These random iris patterns of the iris are very unique and distinct for each human being which makes them ideally suited to be used as a biometric trait in authentication purposes. These patterns are ideally stable in nature and do not undergo any physiological variations during lifetime although it might suffer from slight changes due to problems like glaucoma, conjunctivitis, cataract. The portion of the iris is situated between a liquid substance which is known as aqueous humor and the thin transparent layer formed in the front of the eye known as cornea which gets protected from the environmental dust by the eyelids and eyelashes. These particular characteristics of reliability, stability and consistent nature makes them ideal for research purpose and sophisticated equipments can be employed in iris recognition schemes for authentication purposes which also involve huge capital investments on part of industries and researchers.

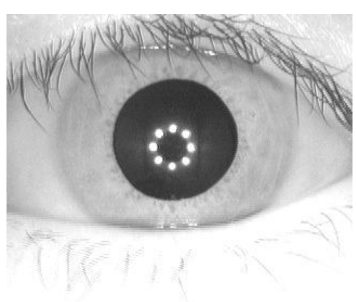


Figure 2.5: Original eye image

2.3.1 Iris Segmentation

In iris recognition systems the major importance lies on the detection of the inner as well as the outer peripheries of the iris texture properly. The prior segmentation methods rely on the modeling of the iris boundaries and the eyelids using simple geometric computations in which the pupil(inner) and the limbus(outer) region are characterized as circular or annular regions and eyelids as the parabolic arcs although the circles are not considered effective for modeling the pupil boundaries. The irregular circumference of the pupil is the main motivation behind devising an accurate pupil detection algorithm using contours for localizing the pupil regions which takes into account the actual pupil boundary which is nearly circular.

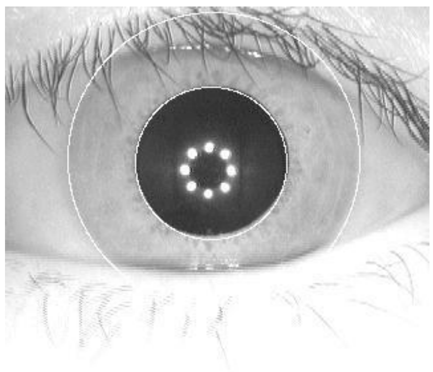


Figure 2.6: Iris segmented

Commonly used techniques for segmentation include the Integro-differential operator given by Daugman, Hough transform and active contour models which are quite efficient in distinguishing the boundary regions.

1. Daugman's Integro-differential Operator

For localization of the iris Daughman had proposed this method. Circular edge detector is operated on the circular boundaries of the iris. An accurate estimation of the contour is done and the integro-differential operator is applied to segregate the lower and upper eyelids to position them. The operator is given by the formula as under:

$$\max(r, x_0, y_0) \left| G_\sigma(r) * \frac{\partial}{\partial r} \int_{(r,x_0,y_0)} \frac{I(x,y)}{2\pi r} ds \right|. \tag{2.9}$$

Input image I(x,y) is taken over which the operator is applied. First the integral is taken at different radii over the normalized region of the iris which is circular and then a partial derivative operation is done. There is a maximization of the integral derivative where there is a sudden variation in the intensity values on the contours. The smoothing function is denoted by $G_\sigma(r)$ which smoothen the intensity for accurate search.

2. Hough Transform

Hough transform is typically used for line formations, getting curves for polynomial functions and circle formations. In circular formations the edges are taken as local pattern and the global pattern is set where the value of hough transform gets maximized. This method was proposed by Wildes and is based on taking derivative of the image. An edge map is taken over the image which involves putting a threshold value over the gradient of the image intensity:

$$|\nabla G(x,y) * I(x,y)|, \tag{2.10}$$

The maximization of the hough transform function is done using edge map over the points (xj,yj) where j=1,2,3,…n. The formula for hough transform is as under:

$$H(x_c, y_c, r) = \sum_{j=1}^{n} h(x_j, y_j, x_c, y_c, r), \tag{2.11}$$

where

$$h(x_j, y_j, x_c, y_c, r) = \begin{cases} 1 & \text{if } g(x_j, y_j, x_c, y_c, r) = 0; \\ 0 & otherwise. \end{cases} \tag{2.12}$$

The parametric function g defines the circular regions of pupil:

$$g(x_j, y_j, x_c, y_c, r) = (x_j - x_c)^2 + (y_j - y_c)^2 - r^2. \tag{2.13}$$

The edge points are found when the value of the above function is zero over the circle having radius r and center as (x_c,y_c). The vertical information is used by limbus and horizontal information given by the eyelids is modeled as parabolic arcs. The hough transform function then finds the local patterns and the parametric function g is transformed to 1.

2.3.2 Iris Normalization

The next step is iris normalization. Most of the normalization techniques involve the transformation of iris into polar coordinates which is known as unwrapping process. Pupil boundary and limbus boundary are mostly non-concentric in nature. Due to this non-concentric property there could be a number of reference points which can be chosen for transformation into polar coordinates. Accurate choice of reference point is of prime importance as the radial and angular information would be defined in reference to this point.

Figure 2.7: Iris normalization into polar coordinates

The normalized image is then decomposed into 1-dimensionsional signal sets. Wavelet transform is applied on each set using Haar wavelet. Sharp intensity variations in the original signal are resultant of the local extrema found in the wavelet transform. Local minimum and maximum are threshold out of the original signal sets. The local minimums and maximums are encoded in a feature vector which is converted to a binary vector which changes value from 1 to 0 at every feature point. Finally a binary vector of the same length as original image is found.

Figure 2.8: Normalized image with signal sets

Hamming distance is used to match the iris codes. The orientation variations are handled by circular bit shifting in any of the vector and minimum distance is computed.

CHAPTER 3

Introduction to Gaussian Mixture Models

3.1 A Brief Review of Multimodal biometric Systems

Fusion in multimodal biometric systems can be performed at four levels namely sensor level, feature level, decision and matching levels. Score level fusion is the most preferred amongst these due to as the fusion is easy and it maintains the data content. The matching scores are available from different systems which are heterogeneous in nature and not consistent with each other. So there is a need for the transformation of these scores to a common range and normalize them which is a challenging task. These scores may be computed on the basis of different similarity measures like Euclidean distance or cosine similarity or having different probability distributions and thus the matching accuracy for each of the systems is varied. Thus due to these reasons it becomes highly difficult to compute a combined vector for these matching scores. The fusion of matching scores is done using transformation techniques, classifier approach and density estimation technique.

1. Transformation or Normalization based Approach: The matching scores are computed using different matchers and then they are normalized to a common range and the combination of the matching score is based on various fusion rules like sum, max, min, product rules. The weights for weighted sum rule are empirically estimated using a correct evaluation of the data.

The rules for fusion are given as under:

i. Sum Rule:

Genuine (SUM_Score)=0.5 {Genuine(Match_Score1)+ Genuine(Match_Score1)}

Imposter (SUM_Score)=0.5 {Imposter(Match_Score1)+ Imposter(Match_Score1)}

ii. Max Rule:

Genuine (MAX_Score)=max {Genuine(Match_Score1), Genuine(Match_Score1)}

Imposter (MAX_Score)=max {Imposter(Match_Score1), Imposter(Match_Score1)}

iii. Product Rule:

Genuine (PROD_Score)={Genuine(Match_Score1)* Genuine(Match_Score1)}

Imposter (PROD_Score)={Imposter(Match_Score1)* Imposter(Match_Score1)}

iv. Weighted Sum Rule:

Genuine(WEIGHTEDSUM_Score)={W1*Genuine(Match_Score1)+ W2*Genuine(Match_Score1)}

Imposter(WEIGHTEDSUM_Score)={W1*Imposter(Match_Score1)+ W2*Imposter(Match_Score1)} and W1+W2=1

where the weights could be estimated using performance indices eg (FAR + FRR)

$$W_1 = \frac{1-(FAR_1 + FRR_1)}{2-(FAR_2 + FRR_2 + FAR_1 + FRR_1)}$$

2. Classifier Approach: In this method, a classifier is used to distinguish the genuine and imposter scores from the matching scores obtained from different matchers which are stored as a feature vectors. As the number of genuine match scores are less as compared to the imposter match scores the training set is not uniform and the complexity for training the genuine score set is of the linear order O(N) and for imposter score it is $O(N^2)$. In an adaptive multimodal biometric system the cost of false acceptance and for false rejection is different. If the CFR=1.9 it means that the FRR should be less. The

system is more favorable to use if the cost is less. Cost is taken in the range [0.1-2]. CFR=2-CFA where CFR is cost for false rejection and CFA means cost for false acceptance. The false acceptance rate should be less than 0.1% for high security applications and FRR should also be minimized for specified threshold to minimize the error rates. Selection and training of a classifier for a given data set which would give an optimal performance and minimize the error rates is a complex task. Thus classifier based approach pose these challenges.

3. Density Evaluation Approach: It involves the estimation of match score densities for genuine and imposter scores. A likelihood ratio test is then performed on the matching scores to get the optimal performance. The density evaluation technique gives the best result if the densities for the matching scores are computed accurately. Kernel Density Estimator is a density evaluator which requires the kernel bandwidth to be known and computation of density at ends of continuous input data is difficult. Gaussian Mixture Models (GMM) is more effective in density estimations. GMM is based on density based score fusion as it estimates the genuine and imposter match score densities. GMM can give a correct estimate for genuine and imposter match scores. It gives a consistently high performance for multimodal biometric data sets so is a useful technique for classification. The sample quality can also be checked using likelihood ratio test.

3.2 Why to use Gaussian Mixture Models?

It is not easy to find that the parametric computation of the copula function which is used in the density estimation and the components of the heuristic which are discrete in nature using kernel density estimator. Gaussian Mixture model can effectively overcome these complications which estimate the densities arbitrarily and the results obtained by the density estimation are very close to the actual estimates of the density in the mixture components. Gaussian mixture models are finite mixture model for classification which is based on supervised learning. Supervised learning and regression models are used to set the parameters of the Gaussian Mixture Models.

The match scores are computed from different matchers and they constitute a randomly selected vector of match scores V= [V1, V2, …, Vn] where N=1,2,….,n are the number of matchers. The conditional joint density is required to be found for n different matchers for both genuine and imposter data sets. D_{gen} and D_{imp} denote the joint density estimates for n different matchers for both the classes for n different matchers. The multivariate Gaussian density function has to be estimated which is based on the parameters mu(mean) and sigma(covariance) given as:

$$\text{Gauss\_Density(v,mu,sigma)}=\frac{1}{\sqrt{2\pi^{n}*(sigma)}}\,exp\left(-\frac{(v-mu)^{T}(v-mu)}{2*sigma}\right) \qquad (3.1)$$

The density estimates for genuine and imposter classes are given as under:

$$D_{gen(v)}=\sum_{s=1}^{Mix_{gen}} w_{gen} * Gauss\_Density(v, mu_{gen,s}, sigma_{gen,s}) \qquad (3.2)$$

$$D_{imp(v)}=\sum_{s=1}^{Mix_{imp}} w_{imp} * Gauss\_Density(v, mu_{imp,s}, sigma_{imp,s}) \qquad (3.3)$$

Where Mix_{gen} and Mix_{imp} denote the mixture composition for genuine and imposter class set and $mu_{gen,s}$ and $mu_{imp,s}$ are mean vectors and $sigma_{gen,s}$ and $sigma_{imp,s}$ are covariance vectors for both classes respectively. The summation of the weight components should correspond to 1. $\sum_{s=1}^{Mix_{gen}} w_{gen} = 1$ and $\sum_{s=1}^{Mix_{imp}} w_{imp} = 1$.

Gaussian Mixture Model is supervised technique which requires some predetermined parameters for classification which are estimated using EM (expectation and Maximization) algorithm. In EM algorithm the estimation of parameters is based on some latent variables which are associated with each input data which requires initial set of some parameters which get fine tuned in every iteration to get the maximize the value of maximum likelihood. It is able to handle missing data as well. . It is intractable to find the maximum likelihood value directly. EM algorithm handles this by solving the linear equation simultaneously. Either the maximum likelihood value is known or we proceed to find the correct estimate of parameters using the latent variables and input data set or using an initial estimate of parameters the maximum likelihood function is found. GMM is better than other density estimators like Kernel Density Estimator (KDE) as it is required to know the kernel bandwidth and computation of density at ends of continuous input data is difficult and GMM can give a correct estimate for genuine and imposter match scores. It gives a consistently high performance for multimodal biometric data sets so is a useful technique for classification. The EM algorithm can also model discrete data by representing the component mixture with a small value of covariance. A regularization component is added to the diagonal value of the matrices which does not change the evaluation in the match score densities.

Density estimation approaches can be categorized as parameter based or non parameter based. Gaussian Density Estimation technique is parametric in nature as the parameters are evaluated given the Gaussian density function estimate using the data. Kernel Density Evaluator are data centric and do not require any density function. The Gaussian Mixture Density Estimation parameters can be known apriori or can be varied as per the data. The non parametric evaluators like the density histogram approach have some drawbacks as it requires a careful estimation for the bin edges and the rate of convergence of the histogram function is low. The density estimation is done using a step function for this method.

3.3 EM(Expectation-Maximization Algorithm)

The EM algorithm recursively finds the estimate of maximum likelihood function based on some latent unobserved values of the variables. It is a statistical approach for maximizing the likelihood function in successive iterative steps. Gaussian Mixture Model is a supervised technique which requires some predetermined parameters for classification which are estimated using EM (expectation and Maximization) algorithm. In EM algorithm the estimation of parameters is based on some latent variables which are associated with each input data which requires initial set of some parameters which get fine tuned in every iteration to get the maximize the value of maximum likelihood. It is able to handle missing data as well. GMM is based on density based score fusion as it estimates the genuine and imposter match score densities. It is intractable to find the maximum likelihood value directly. EM algorithm handles this by solving the linear equation simultaneously. Either the maximum likelihood value is known or we proceed to find the correct estimate of parameters using the latent variables and input data set or using an initial estimate of parameters the maximum likelihood function is found.

The algorithm keeps switching between the E-step in which the likelihood function is found and M-step which finds the parameters which maximize the likelihood function evaluated in the E-step. There is an association of the input data with the latent variables corresponding to each mixture component. The MLE (maximum likelihood estimation) is done by taking the derivatives of the likelihood function along all the parameters (unknown and latent variables). The substitution of one parameter set into other does not solve the equation. Thus the equations are solved simultaneously. One of the possible solution is two arbitrarily assume the value of one set of unknowns and substitute them to find the value of second set of unknowns and then prune the first set using the solution for second set till the convergence point is reached with the optimal values for both the set of unknowns. In case of multiple maximas we get stuck in the local maximum value of likelihood function and do not find a global maximum.

The EM algorithm is applicable for discrete and continuous input data sets which may be infinite in number and for finite number of latent variables where each latent variable corresponds to an unobserved data value. The parameter sets are continuous in nature which may be associated to all the input data points or to a single latent variable. When the parameter data set is known then the value of the latent variables could be estimated by maximizing the loglikelihood function for all possible values of latent variables L or vice versa i.e. finding the parameter set if latent variables are known. Firstly the parameters are empirically estimated to any random value. The best value of L latent variable set for these parameters is computed. Then the L values are used to get a better result of the parameter sets by iterating the same process a convergence point is reached. The k-means clustering algorithm is classified as hard EM method as they approach a local minimum value of the objective function.

E-Step: $L(\theta,\theta^{(i-1)})=E[\text{log-likelihood}_P(D,UD|\theta)|D, \theta^{(i-1)})=\int log_p(D,UD|\theta)|D,\theta^{(i-1)}\,dy$ (3.4)

M-Step: $\theta^i=\text{argmax}(L(\theta,\theta^{(i-1)})$ (3.5)

where L: log likelihood function, θ: next parameter set, $\theta^{(i-1)}$: current parameter set, D:observed data set, UD: unobserved data set

3.4 Likelihood Ratio

Neymann-Pearson had proposed this likelihood ratio test. $D_{gen(v)}$ and $D_{imp(v)}$ denote the joint density estimates for n different matchers for both the classes for n different matchers. Then the genuine and imposter classification can be done by taking the ratio of the density functions. The hypotheses considered are H_0: v is imposter score and H_1: v is genuine score. FAR is the probability that the system incorrectly matches the input pattern to a non-matching template in the database and FRR is the probability that the system fails to detect a match between the input pattern and a matching template in the database. When the ratio of $\frac{\text{Dgen(v)}}{\text{Dimp(v)}} > threshold$ it is a genuine score else imposter score.

CHAPTER 4

Support Vector Machines

4.1 Overview

Machine Learning is a branch of artificial intelligence which requires the learning of the system by the training data. In an email system in order to segregate the spam and non spam related messages machine learning approaches could be employed which will train the system on the basis of some email messages and then classify the next incoming messages into separate folders. Thus, machine learning techniques are widely used in classification and regression problems. The classification and regression analysis are used in statistics. In regression analysis, the association between various dependent and independent variables is analyzed and a relationship is established between these variables and how the value of dependent variable changes with the change in the values of any of the independent variable. In classification analysis, the initial training of the data set is required whose membership values are already known i.e to which class it belongs and the new observations of the input vector set can then be classified based on the learning of the system. The new input data set is categorized on the basis of some properties which are explanatory set of variables which can be integer valued or real valued, categorical data or ordinal data. Some of the machines learning algorithms are based on the discrete data classification where the input set is discretized into any of the group sets or classes e.g.: The diagnosis results of a patient are classified into different medical ailment set on the basis of some properties like gender of the patient, blood pressure values and symptoms of diseases. Classification is considered as a supervised machine learning problem as the training of some observation sets is already available. Clustering is unsupervised learning approach as it involves the grouping of the data set based on some similarity measure.

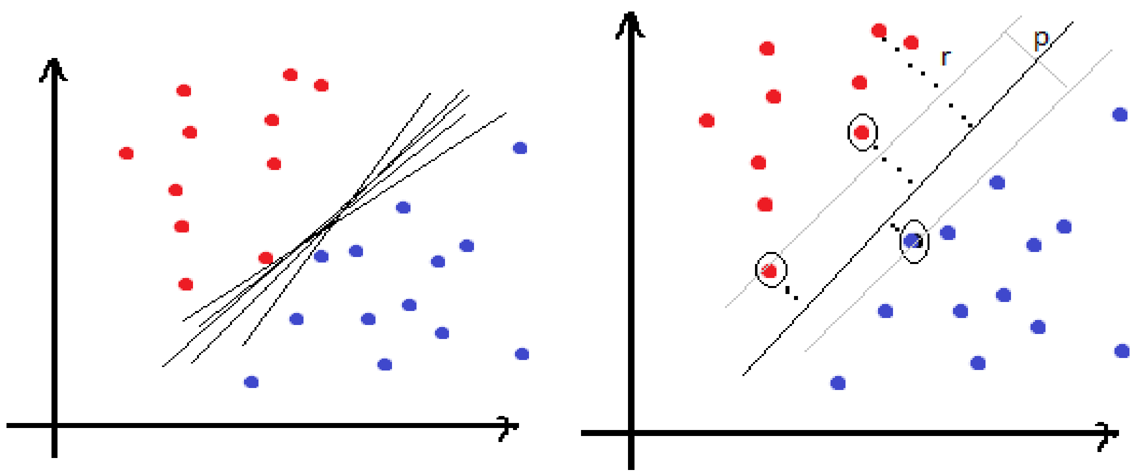
Machine learning techniques find huge applications in the industry particularly in computer vision field and pattern recognition applications. In supervised learning techniques the input data set is mapped to its corresponding label or class based on the learning whereas in unsupervised learning clustering of the input data set is done. In semi-supervised learning techniques both labeled and non labeled data sets to define the functionality of the classifier. SVM(Support

Vector Machines) are a part of binary classification which classifies each data input as belonging to the class or not based on the training data sets.

4.2 Support Vector Machines

4.2.1 Introduction

SVM (Support Vector Machines) are active learning technique which is a binary classification technique in which the input data set is classified into any of the two classes or groups based on the apriori known classification of the training data based on a certain decision rule set. SVMs do a matching of the training data into high dimension feature set implicitly. The input data is segregated into two classes based on the hyperplanes or decision surfaces that are constructed and the distance is maximized between hyperplanes and points lying near them which are known as support vectors. Thus these decision surfaces help in the classification.

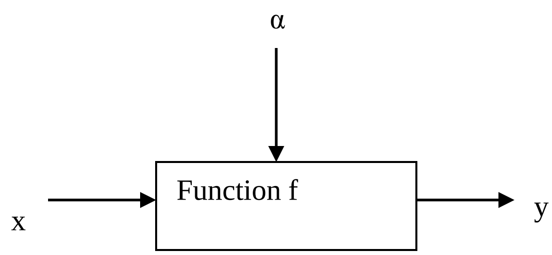


a) b)

Figure 4.1: a) number of linear separators segregating the data b) Maximum margin classifier

The decision of choosing the hyperplanes is very difficult as it is difficult to find that which of them gives optimal results. Classification margin is identified for the choice of the separator. The points which are closest to the hyperplane are known as support vectors. Margin ρ is the distance between the support vectors along the separator or the hyperplane. The margin should be maximized in order to get the correct results.

The linear support vector machine can be mathematically denoted as:



$f(x,w,b)=\text{sign}(wx+b)$ (4.1)

There is a training set data $\{x_j,y_j\}$ where $j=1,2,..,n$, $x_j \epsilon$ R where R is a set of Real numbers and $y_j \epsilon[-1,1]$ and the data is separated by a hyperplane with margin ρ. For each training sample x_j,y_j the following conditions are satisfied:

$w^T x_j+b \leq -\rho/2$ if $y_j=-1$ (4.2)

$w^T x_j+b \geq -\rho/2$ if $y_j=+1$ (4.3)

which implies $y_j(w^T x_j+b) \geq \rho/2$ (4.4)

This above inequality changes to equality for every support vector denoted by x_s. In the equality if we rescale the values of w and b by ρ/2 the distance between each support vector x_s and the hyperplane would be given by :

$\text{Dist}= y_s(w^T x_s+b)/|w|=1/|w|$ (4.5)

and the margin ρ can be given by $\rho=2*\text{Dist}=2/|w|$ (4.6)

Maximizing the margin $\rho=2/|w|$ is same as minimizing the value $0.5\ w^T w$.

The quadratic optimization problem is formulated as which also gives the solution for w and b:

Minimize $\phi(w)= 0.5\ w^T w$ subject to $y_j(w^T x_j+b) \geq 1$ for all j values.

A number of algorithms exist for solving this well known class of typical mathematical programming quadratic optimization problem which is subjected to linear constraints. The solution involves the association of a Langrange multiplier α_j with every constraint in the initial problem which results in the construction of a dual problem as:

We need to find $\alpha_1 \ldots \alpha_n$ such that

$Z(\alpha)=\sum \sum -1/2 \sum\sum \alpha_i \alpha_j y_i y_j x_i^T x_j$ to be maximized

For $\sum \alpha_j y_j=0$ and $\alpha_j \geq 0$ for all α_j.

Solving of the optimization problem involves computing the inner product $x_i^T x_j$ between all the training point pairs.

Support Vector Machines essentially reduces the structural risk factor and overcomes the problems of over fitting of the data. Over fitting refers to the noisy data classification along with original data. Hard Margin refers to the classification of the data points correctly with no training error and soft margin is used for the classification of difficult and noisy data by the introduction of slack variables ξi.

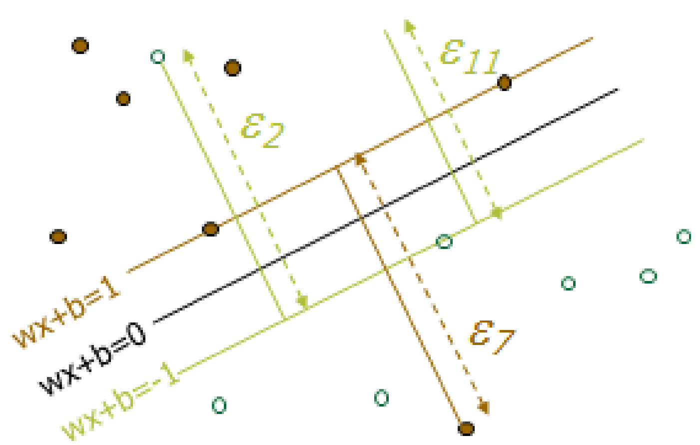


Figure 4.2: Soft Margin Classification

Now the quadratic optimization criteria become:

$1/2\ w^T w + C\sum_{k=1}^{R} \varepsilon^k$ where parameter C is a parameter to control overfitting problem.

In non linear classifiers the input space is mapped to a high dimensional feature space when the training data set is separable.

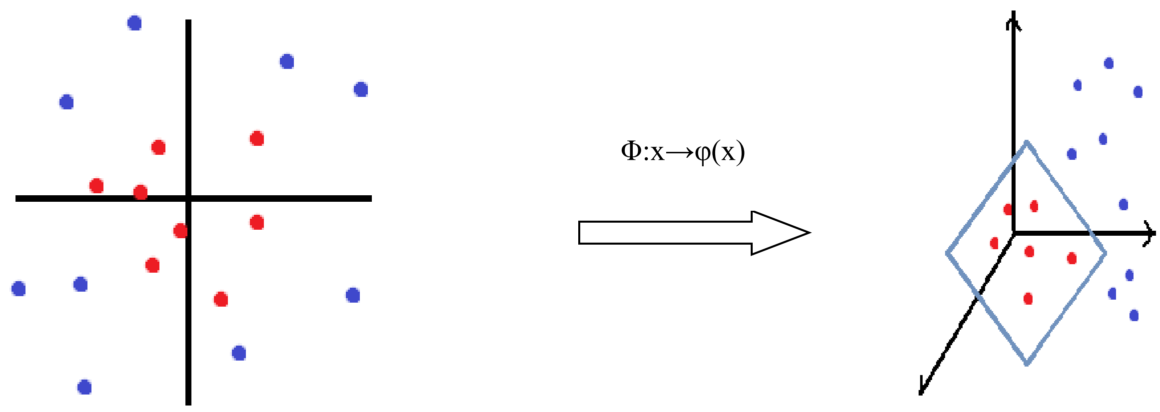


Figure 4.3: Non Linear SVMs

The linear classifiers is based on the dot product between the support vectors $Q(x_i, x_j)= x_i^T x_j$. In non linear classifiers the mapping of every data point in high dimensional feature set takes place based on the transformation function $\Phi:x\rightarrow\varphi(x)$ and then the dot product becomes $Q(x_i, x_j)= \varphi(xi)^T \varphi(x_j)$. A kernel function characterizes a function corresponding to the inner product in the high dimensional feature space. For some kernel functions $Q(x_i, x_j)$ checking $Q(x_i, x_j)= \varphi(xi)^T \varphi(x_j)$ is quite difficult. According to Mercer's theorem it is stated that every kernel is a semi positive symmetric function which correspond to semi positive gram function given by:Q=

$Q(x_1, x_1)$	$Q(x_1, x_2)$	$Q(x_1, x_3)$	…	$Q(x_1, x_N)$
$Q(x_2, x_1)$	$Q(x_2, x_2)$	$Q(x_2, x_3)$	…	$Q(x_2, x_N)$
…	…	…	…	…
$Q(x_N, x_1)$	$Q(x_N, x2)$	$Q(x_N, x_3)$	…	$Q(x_N, x_1)$

Types of Kernel functions:

1. Linear Function: $Q(x_i, x_j)= x_i^T x_j$ (4.7)
2. Polynomial Kernel Function with power p: $Q(x_i, x_j)= 1+(x_i^T x_j)^p$ (4.8)
3. Gaussian /Radial basis function : $Q(x_i, x_j)= \exp(-(x_i- x_j)^2/2\sigma^2)$ (4.9)

4. Sigmoid function: $Q(x_{i,} x_j)= \tanh(\beta_0 x_i^T x_j+ \beta_1)$ (4.10)

Non Linear SVMs can be solved by the dual problem as:

We need to find $\alpha_1 \ldots \alpha_n$ such that

$Z(\alpha)=\sum \sum -1/2 \sum\sum \alpha_i \alpha_j y_i y_j Q(x_{i,} x_j)$ to be maximized

For $\sum \alpha_j y_j=0$ and $\alpha_j \geq 0$ for all α_j.

The solution is given as

$F(x)= \sum \alpha_j y_j Q(x_{i,} x_j)+b$

The optimization techniques for finding α_j's are the same.

4.2.2 Properties of choosing SVMs

There is flexibility in the choice of the similarity function. There exists a sparse nature in the solution which is generated when we have a large data and is separated by hyperplanes or decision planes. Support vectors specify these hyperplanes. It is possible to handle large feature sets using support vectors without the need for the dependence on dimensionality of the feature space for finding the complexity of the system. Over fitting of data problem is handled by the soft margin approach. Convex optimization problem leads to a single global solution set.

4.2.3 Applications of SVMs

Support Vector Machines finds a number of applications in real life problems like text and image classification, protein and cancer classification problems in bioinformatics field, hand written character recognition. SVM is more sensitive to noise as a few numbers of mislabeled points can also reduce the performance heavily. It considers only two class classification. Multiclass classification can be done using SVMs by training n no of SVMs if we want n-ary classification. For finding the output for any new data point prediction with each SVM needs to be done and we select the SVM with most positive region output. Text categorization is related to the classification of natural text into different categories based on their content search. It is useful in web based searching, keyword based content mining, email sorting. A document might get assigned to more than one specific category so it is a multiple binary classification problem.

Chapter 5

RESULTS AND DISCUSSION

5.1 Preview

The experimentation in this work is carried out with two publicly available palmprint and knuckleprint databases: Hong Kong Polytechnic University (PolyU) Palmprint Database and IITD database. The iris database is taken from the standard CASIA database.

The FAR that was chosen for the experimental work was 0.01 for palmprint authentication. The results after the application of the 3 detectors were best for Harris detector followed by SIFT detector then HOG. The results were significantly good for the Harris detector at scale 8. Gar was around 100% for Harris detector and approximately 98% for SIFT detector which was quite high as compared to prior techniques which did not work well with contact-less databases.

5.2 Results Using GMM

Experiment 1. GMM results on Iris and Palmprint Databases

The iris database consisted of 175 users. The genuine and imposter scores were calculated using Hamming Distance to match the iris codes. EM algorithm was employed to get the results of the parameters which were used to find the probability density functions for genuine and imposter scores. The genuine and imposter multivariate Gaussian pdfs were thresholded to get the performance measures of FAR and FRR to get the ROC curve. The GAR was 79% for FAR=0.1.

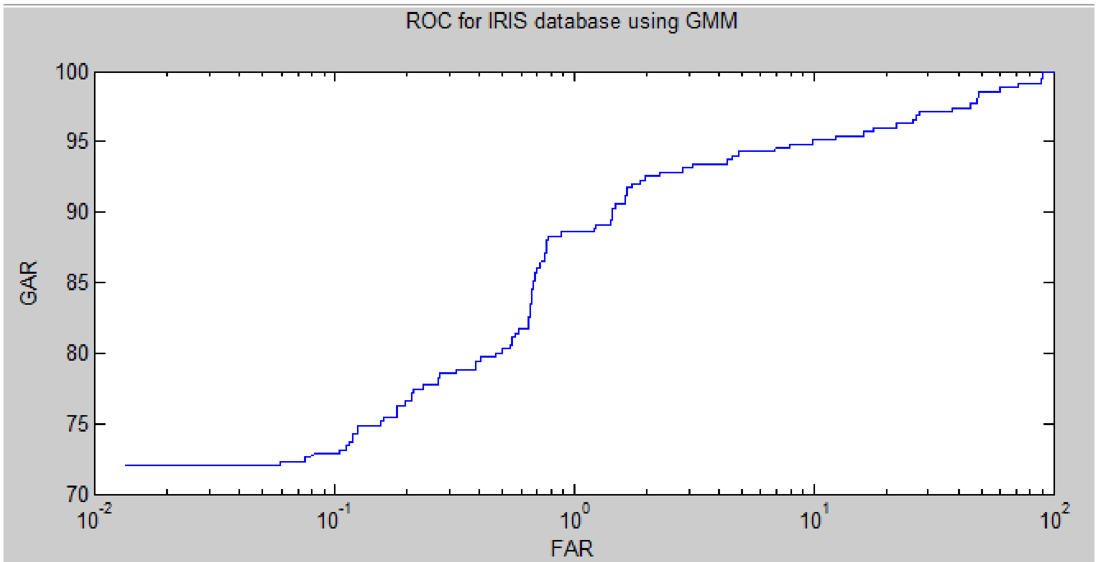


Figure 5.1: ROC curve for Iris database using GMM.

The Gaussian pdfs were calculated for the palmprint database scores and the ROC results were plotted. The GAR was 70% at FAR=0.1

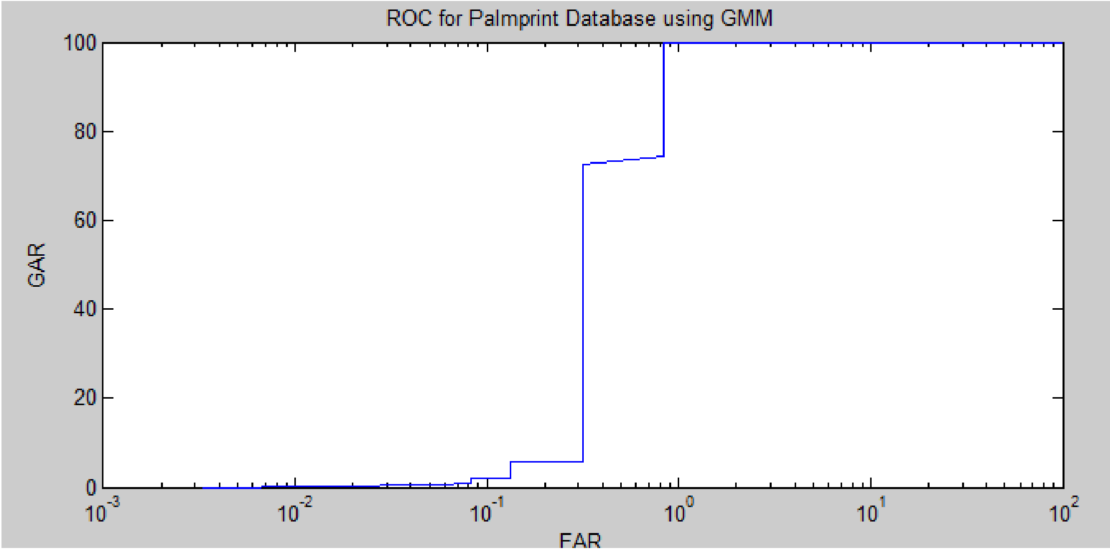


Figure 5.2: ROC curve for Palm database using GMM.

The scores obtained from the two databases were fused to get combined genuine and imposter scores. GAR calculated at FAR=0.1 was 92% which was quite high.

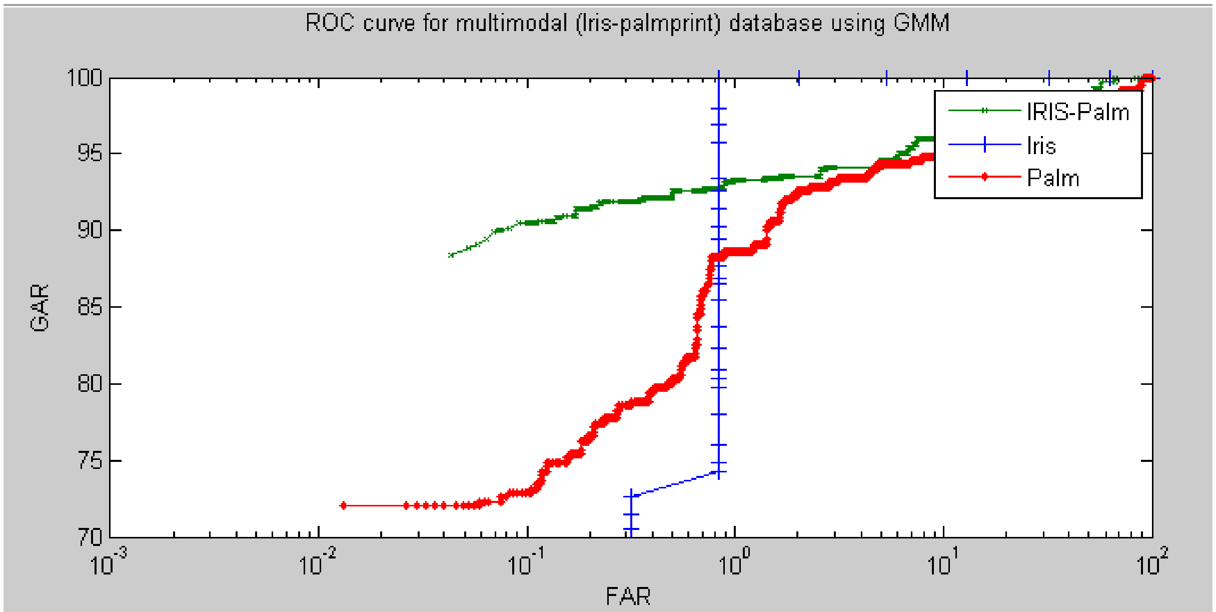


Figure 5.3: ROC curve for Iris-palmprint database using GMM.

Database Used	**No. of Components in genuine scores**	**No. of Components in imposter scores**	**GAR** (at FAR 0.1)
Iris	12	15	79
Palm	12	3	70
Iris_Palm	12	9	92

Table 5.1: Iris_palmprint Database performance measures using GMM

Experiment 2. GMM results on Palmprint-IITD Database

The scores obtained by SIFT and Harris on IITD database without the application of gabor filter were fused for genuine and imposter at score level.

Results after application of EM algorithm for implementing Gaussian Mixture Model:

Steps for EM algorithm:

1. Randomly the values of mean and variance (parameter set ϕ) are estimated initially.
2. For each data point a responsibility value r is associated with it.
3. $r_{i,k}$ denotes that the likelihood of i^{th} point belonging to the k^{th} mixture.
4. Now each data point gets associated to a responsibility value r ∈[0-1] as { $r_{i,1}, r_{i,2}, \ldots, r_{i,k}$}.
5. Using r the weighted mean and variance of each Gaussian model is computed.
6. We get the new parameter set and iterate the process of finding new r and new ϕ.
7. EM algorithm consists of the expectation and maximization steps.

For genuine distribution of the palmprint scores are obtained from SIFT and HARRIS

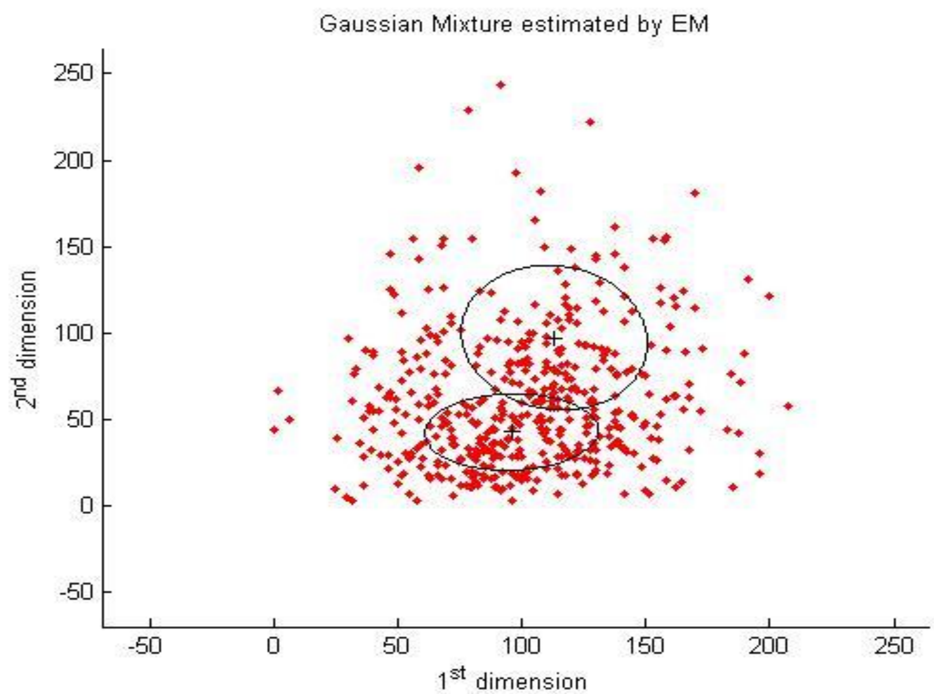


Figure 5.4: Results after EM algorithm on the scores of genuine distribution of IITD database from Sift and Harris(scale 8) scores of the palmprint database.

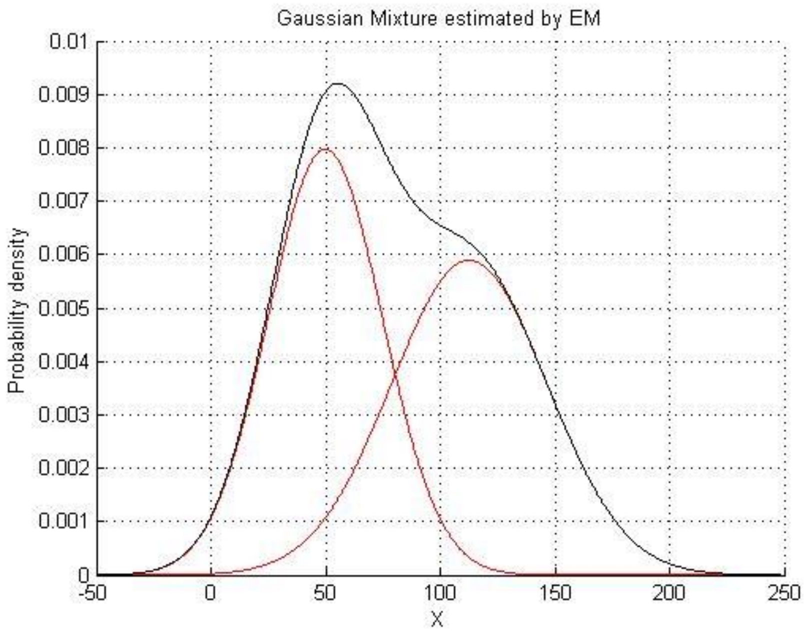
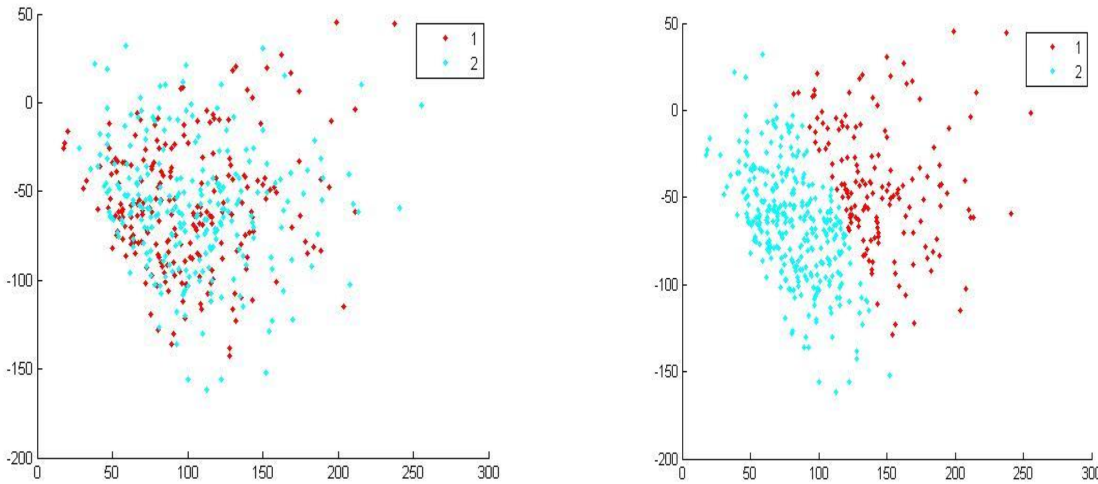


Figure 5.5: Gaussian PDF of the mixture.



a) b)

Figure 5.6: Results after application of EM algorithm which classifies the data into the clusters of the components of the mixture a) before EM algorithm b) after EM algorithm on the scores of genuine distribution of IITD database from Sift and Harris(scale 8) scores of the palmprint database.

ROC of SIFT and Harris scores are given in Figure 5.7 and 5.8. The GAR for SIFT is 99.1% and Harris is 99.35 for FAR=0.1.

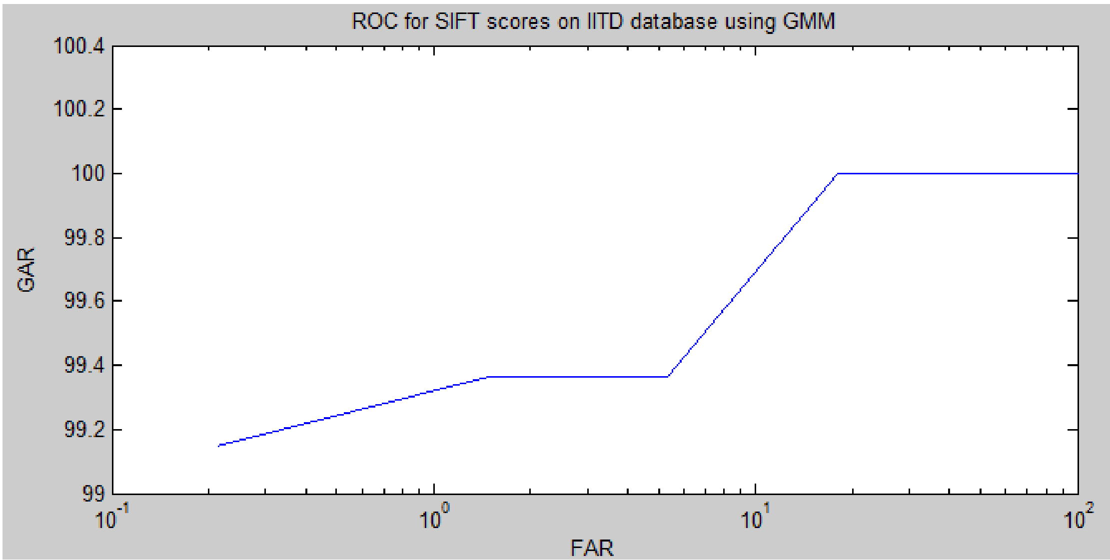


Figure 5.7: ROC for IITD database on SIFT score using GMM

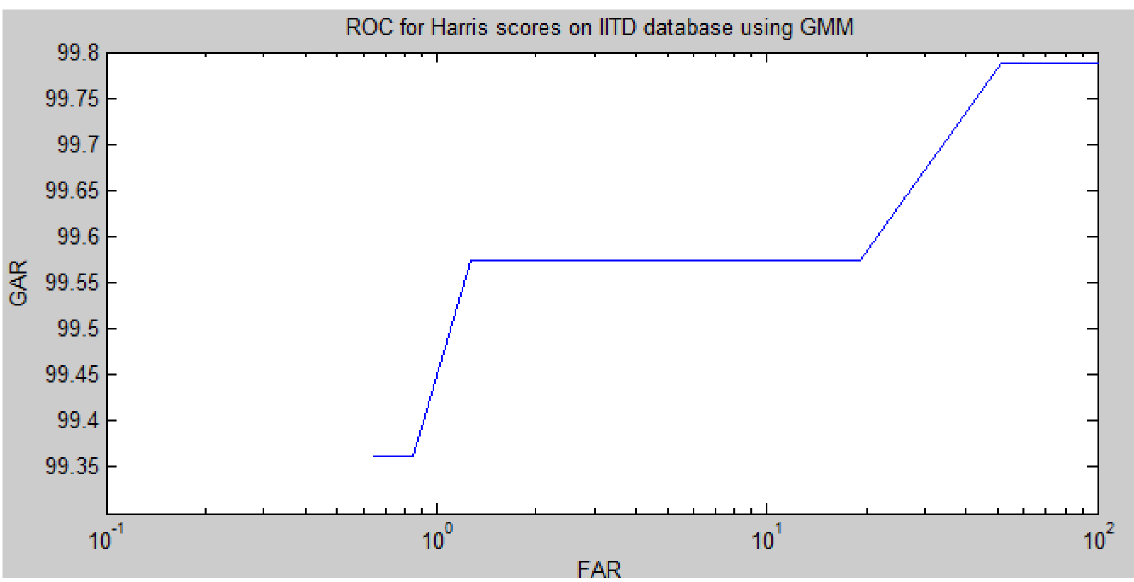


Figure 5.8: ROC for IITD database on Harris score using GMM

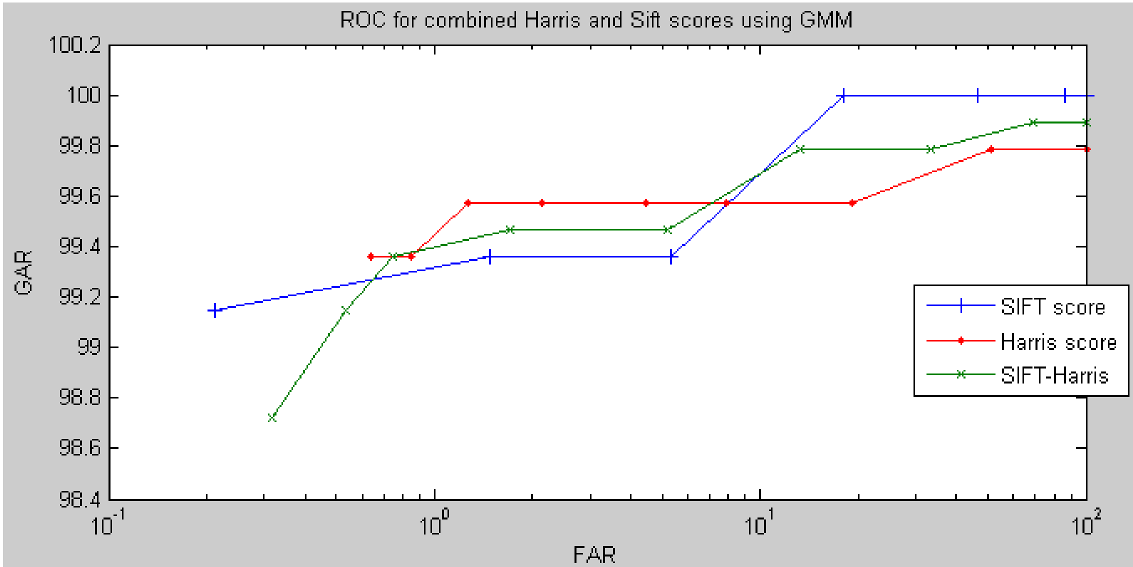


Figure 5.9: ROC for IITD database on combined score using GMM

Database Used	**No. of Components in genuine scores**	**No. of Components in imposter scores**	**GAR** (at FAR 0.1)
SIFT score	3	5	99.1
Harris score	10	3	99.35
Combined score	9	5	98.7

Table 5.2: Palmprint Database performance measures using GMM

Experiment 3. GMM results on Palmprint-PolyU Database

The no of users is 235. On the palmprint database the Gabor filter was applied in order to improve the textural features. The parameters used for the Gabor filter are $\theta = \pi / 4, \sigma = 5.6179, u = 0.0916$. The images obtained after convolving Gabor filter are named as GROI (Gabor-Region of Interest). The GROI images were matched using hamming distance.

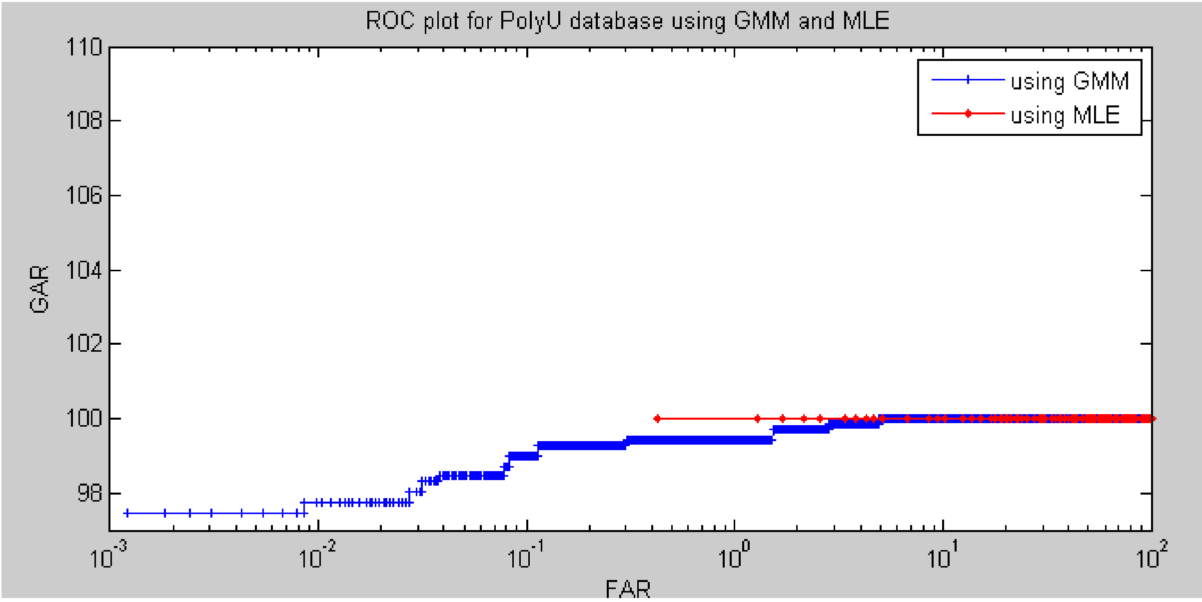


Figure 5.10: ROC for PolyU database on gabor convolved images matched by hamming distance scores using GMM and MLE

The genuine and imposter scores were divided into training and test sets. For every 5 samples corresponding to each users were divided into 2 sets 2 samples and 3 samples. Out of the 3 sample set 1 was taken as training data and 2 as test data.

The no of samples in training set was

Genuine training=235

Imposter training=235*234=54990

The no of samples in test set was

Genuine training=235*2=470

Imposter training=235*234*2=109980

The MLE was computed for the test data of genuine and imposter scores and was compared to a threahold value to give the performance measures.

5.3 Results of Support Vector Machine

Experiment 1. SVM results on Palmprint-PolyU Database

The PolyU database was considered for experimentation. The number of users is 235. The genuine and imposter scores were divided into training and test sets. For every 5 samples corresponding to each user were divided into 2 sets 2 samples and 3 samples. Out of the 3 sample set 1 was taken as training data and 2 as test data.

The no of samples in training set was

Genuine training=235

Imposter training=235*234=54990

The no of samples in test set was

Genuine training=235*2=470

Imposter training=235*234*2=109980

The training sample was trained using a label in SVM which treats the not a number and empty strings as missing data and gives a svm structure element with the fields having support vectors, alpha, bias, kernel functions, kernel function arguments, group names, support vector index, scaling data.

Kernel function could be linear which uses the dot product or quadratic kernel. Gaussian radial basis function takes default kernel with sigma 1. Polynomial kernel is of the order 3. Multilayer Perceptron kernel has sigma and bias in the range {-1, 1}. The error rates for Gabor convolved images which were matched using hamming distance and hog data are given in the Table 5.3.

The scores were normalized using different fusion rules:

i. Sum Rule:

Genuine (SUM_Score)=0.5 {Genuine(Match_Score1)+ Genuine(Match_Score1)}

Imposter (SUM_Score)=0.5 {Imposter(Match_Score1)+ Imposter(Match_Score1)}

ii. Product Rule:

Genuine (Prod_Score)= {Genuine(Match_Score1)* Genuine(Match_Score1)}

Imposter (Prod_Score)= {Imposter(Match_Score1)* Imposter(Match_Score1)}

Data-Gabor Hamming			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	7	94
120	0.0105	6.6667	94.1667
170	0	6.4706	94.1176
Data-HOG			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0.0051	3.5000	98
120	0.0070	2.0833	97.9167
170	0.0052	3.2353	97.6471
Data-Sum Rule(Gabor Hamming data+Hog data)			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	4	97.5
120	0.0245	2.0833	97.9167
170	0	2.6471	97.6471
Data-Product Rule(Gabor Hamming data+Hog data)			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	4.5000	98
120	0.0210	1.6667	96.6667

170	0	2.6471	96.7647

Table 5.3: PolyU Palmprint Database performance measures using SVM

In SVM some membership values can also be assigned to the training samples and this hard conditioning of the membership values can be used to classify the test data. The results are given in Table 5.4.

Data-Gabor Hamming			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	7	93
120	0.0105	8.3333	91.6667
170	0	7.6471	92.3529
Data-HOG			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	7	93
120	0	5.4167	94.5833
170	0	7.3529	92.6471
Data-Sum Rule(Gabor Hamming data+Hog data)			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
100	0	6	94
120	0	4.5833	95.4167
170	0	5.2941	94.7059
Data-Product Rule(Gabor Hamming data+Hog data)			

No. of Users	FAR	FRR	GAR=100-FRR
100	0	4.5000	95.5000
120	0	1.6667	98.3333
170	0	2.6471	97.3529

Table 5.4: PolyU Palmprint Database performance measures using SVM with membership values

Experiment 2. SVM results on Knuckleprint-PolyU Database

The PolyU database was considered for experimentation. The number of users is 165. The genuine and imposter scores were divided into training and test sets. For every 5 samples corresponding to each user were divided into 2 sets 2 samples and 3 samples. Out of the 3 sample set 1 was taken as training data and 2 as test data.

The no of samples in training set was

Genuine training=165

Imposter training=165*164=27060

The no of samples in test set was

Genuine training=165*2=330

Imposter training=165*164*2=54120

The error rates for gabor convolved images which were matched using hamming distance and hog data and with the fusion rules are given in the Table 5.5.

Data-Gabor Hamming			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	0	20	80
20	0	25	75
100	0.0202	53	47
150	0	47.3333	52.6667
Data-HOG			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	0	13.3333	86.6667
20	0	7.5000	92.5
100	0	12	88
150	0	12	88
Data-Sum Rule(Gabor Hamming data+Hog data)			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	0	16.6667	83.3333
20	0	12.5000	87.5
100	0	25.5000	74.5
150	0	23.3333	76.6667
Data-Product Rule(Gabor Hamming data+Hog data)			

No. of Users	FAR	FRR	GAR=100-FRR
15	0	13.3333	86.6667
20	0	10	90
100	0	24	76
150	0	22.6667	77.3333

Table 5.5: PolyU Knuckleprint Database performance measures using SVM

The results for knuckle database using membership values on the data using SVM are given in Table 5.6.

Data-Gabor Hamming			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	16.6667	6.6667	93.3333
20	7.3684	15	85
100	0	60	40
150	0	56.6667	43.3333
Data-HOG			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	2.3810	0	100
20	0	5	95
100	0	21	79
150	0	21.6667	78.3333
Data-Sum Rule(Gabor Hamming data+Hog data)			

No. of Users	FAR	FRR	GAR=100-FRR
15	4.5238	0	100
20	0.2632	7.5000	92.5
100	0	32.5000	67.5
150	0	32	68
Data-Product Rule(Gabor Hamming data+Hog data)			
No. of Users	**FAR**	**FRR**	**GAR=100-FRR**
15	7.1429	0	100
20	0.9211	5	95
100	0	31.5000	68.5
150	0	32	68

Table 5.6: PolyU Knuckleprint Database performance measures using SVM with membership values.

CHAPTER 6

Conclusion and Future Work

All these techniques discussed for palmprint and knuckleprint above could work well for the contact-less databases. GMM and SVM techniques were applied on the scores obtained from these techniques and showed considerably good results. For multimodal databases GMM could work well as it gave GAR=92% for iris and palmprint traits. In multimodal biometrics based on different matching algorithms also the results were high GAR=98.7% for Harris and SIFT fused scores. MLE could further improvise the results of GMM. In SVM which is a supervised learning technique the training of the data was first done and the test data was classified on its basis. The results were quite good for individual score level and the fused scores which were fused at score level using different rules like Sum rule and Product Rule. Membership value based on some weights was assigned to the data and the results were analysed. This hard conditioning of data also produced significantly good results. For further improvement of the performance of these feature detectors, future work will focus primarily on finding new and more efficient techniques for contact-less databases and a fused classifier GMM-SVM based which can also work with other biometric modalities like vein, knuckle etc.

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