2. Literature Survey

We have seen different biometric traits, types of unimodal & multimodal biometric systems, fusion techniques in the previous chapter. As we have discussed earlier the main consideration is to use image processing technique to develop unimodal and multimodal biometric systems. In this section we will review research in the field of biometrics. We present different biometric traits along with the contributions of different researchers in pre-processing, feature extraction, matching, and classification and experimentation stages of biometric recognition. For the research we have selected biometric traits from the list as previously discussed and grouped them in three groups. First group consists of biometrics present on hand they are Fingerprint, Palmprint & Finger-knuckle print. Second group consists of Face & Iris. The third group has dynamic & static signature recognition.

2.1 Fingerprint, Palmprint & Finger-knuckle Print

Fingerprint, palmprint & finger-knuckle print are the biometric traits found on human hand. These biometric traits are rich in texture, and this information can be extracted to generate a feature vector [1], [3], [4]. We need to capture the data first and then preprocess the data. These stages are common in almost every biometric trait and in case of fingerprint, palmprint and finger-knuckle print they tend to be similar [1], [3], [8], [9]. We discuss the different methodologies for this here.

2.1.1 Fingerprint Recognition Systems

The Automatic Fingerprint Recognition Systems require a clear noise free fingerprint in order to process it for minutiae detection or correlation [29]. This is done by preprocessing the fingerprint image.

2.1.1.1 Fingerprint Preprocessing

The fingerprint must be preprocessed to remove the effect of noise, effect of dryness, wetness of the finger and difference in the applied pressure while scanning the fingerprint. The preprocessing is a multi-step process. The different steps in preprocessing are as follows [29], [30], [31], [38].

1. Smoothening Filter
2. Intensity Normalization

3. Orientation Field Estimation
4. Fingerprint Segmentation
5. Ridge Extraction
6. Thinning

Depending on the application and feature extraction method these steps may vary. Wu and Govindaraju [32] have proposed an adaptive image filtering method for singularity (minutiae) preservation. They first estimated image quality by Fourier spectrum of the image, in this paper, fingerprint images preprocessing is performed based on the discriminant frequency and statistical texture features. Later Gaussian filtering is used to enhance the ridge structure and gradient field coherence strength is used for segmentation of region of interest (ROI).

A Short Term Fourier Transform (STFT) based image filtering is discussed by Chikkerur & Govindaraju [37] to enhance fingerprint images. Another approach widely followed is based on Gabor Filter, Gabor filters capable of directional filtering of ridges. The directional band pass Gabor filter-bank approach is one of the most effective and mathematically elegant techniques to date for fingerprint image enhancement, this fact is used by various researchers for fingerprint image enhancement & segmentation [33], [34], [35], [36]. Like directional Gabor filters Sherlock et al. have proposed directional Fourier filters for filtering fingerprint ridges.

The performance of Gabor filter or any other directional filtering depends upon the direction of filter, which should be properly tuned to ridge direction, for this the orientation estimation is important. Most widely used approach is to go through the gradients of grey intensity [39]. There are some other methods available in literature like filter-bank based approach, spectral estimation, waveform projection, however the gradient based method provide better results [36], [39]. Gradient based technique also have variations, researchers have proposed different ways to estimate orientation form gradients. Lee et al. has proposed a simple technique based on direct calculation of orientation based on gradient in [40]. In [41], [42] authors have discussed orientation estimation based on Eigen values of local structure tensor. Bazen [41] has discussed PCA & Structure tensor based orientation estimation algorithm based on gradients. Mehtre [42] have proposed a modified technique based on gradient calculation which exploits the fact that the orientation field tend to be continuous in the neighboring regions, he has proposed an algorithm which assigns the orientation of central point based on the orientation of neighboring blocks at four corners and their field strength also called as coherence.

Hong et al. [47] discussed a mechanism to achieve a smoother orientation field by a continuous vector field approach. They use an averaging filter to the continuous vector filed calculated from the local gradient angle. Both the approaches give reasonably good approximation of the orientation field. We have proposed an algorithm for orientation estimation based on optimized neighborhood averaging of gradient fields [44]. This algorithm achieves smoother orientation field by gathering information from neighborhood.

Fingerprint segmentation consists in the separation of the fingerprint area (foreground) from the background [29]. Segmentation techniques exploit the existence of an oriented periodical pattern in the foreground, and a non-oriented isotropic pattern in the background. The method described by Jain et al. [39] is based on the local certainty level of the orientation field, which is computed using the intensity gradient of the image. Those 16×16 pixel blocks in which the certainty level is higher than a given threshold are considered as foreground blocks. Maio & Maltoni [40] proposed that the average gradient on each block is computed, which is expected to be high in the foreground (ridge valley variations) and low in the background. Bazen and Gerez have proposed a method [41] where other parameters (gradient coherence, gray intensity mean and variance) are also used in the segmentation decision. A morphological post-processing is also performed in order to fill the remaining holes in the foreground and/or in the background. This method is very accurate but involves high computational burden. The technique presented by Mehtre [42] relies on the gradient and results in lower computational burden. It computes the gray level variance across the normal direction of the orientation field, which is expected to be high in presence of ridge-valley variation. This method is implemented in other fingerprint verification systems as well [43].

The segmentation technique presented by Shen et al. [44] is based on Gabor filters. It computes the response of eight oriented Gabor filters to determine whether a block belongs to the foreground or to the background. It is shown that when good quality images are considered, both gradient- and Gabor-based methods produce similar results, but Gabor filter-based methods are faster than gradient-based approaches. In the present work, an enhanced Gabor filter-based approach is presented. Alonso, Fierrez et al. [35] have proposed an enhanced approach for fingerprint segmentation based on the response of eight oriented Gabor filters .This method obtains higher foreground size and considerably lower size of the background region, thus recovering blocks with minutiae and valid but not well defined zones. A shortcoming of this method is that the thresholding is not automatic and a manual threshold needs to be selected empirically. We have proposed automatic thresholding based on Gabor filters [45]; the process is automated by generating a threshold by Otsu's method [46] applied on Gabor magnitude histogram.

In Correlation [48], [50] based fingerprint recognition system we need to determine a registration point as a reference; this is called as core point. Core point detection is a non-trivial task. In our research we are discussing correlation based fingerprint recognition; now we discuss some methods for core point detection. A. K. Jain, S. Prabhakar et al. have performed Core Point Detection using Integration of Sine Component of the Fingerprint Orientation [47], [48]. In this method the sine component of the orientation filed is integrated in a semicircular region, with three segments and the components are linearly summed up in a specific manner as discussed in [29], this method give a good approximation of fingerprint but accuracy is still low, and for better approximation more number of iterations are required.

They have discussed another approach based on calculation of Poincare index of all the points in orientation map, they actually determine the Poincare index by calculating the consecutive points field angle difference and summing it, the point enclosed by a digital curve (Core Point) will have highest Poincare index. The Poincare Index map is then thresholded and the point with highest value is taken as core point. This method is also used by Afsar F. et al. [49]. This method is also recursive, if no core point is found then the orientation field is smoothened and again the same procedure is followed. If still core point is not estimated then the authors have suggested a covariance based method, but this is computationally expensive.

A Core Point Estimation method using Direction Codes and Curve Classification is developed by C. V. Kameswara Rao, K. Balck [50].

In this method first the orientation field is calculated, from this field the directional codes are generated. The direction codes are used for rough estimate and a sampled matrix is generated. This matrix and curve classification method similar to chain codes is used for accurate core point detection. This method requires more steps and the procedure given in this paper is not suitable for arch type prints, since it is not possible to define the core point in this case. S. Chikkerur, N. Ratha [51] have used Complex convolution map for core and delta points over the squared orientation field to obtain the core and delta point in the fingerprint. This method covers detection of core as well as delta points, and it is a multistep process. The accuracy obtained is good around 95 -98 %. At the same time the mathematical complexity is high and the method needs post processing steps also. We have developed a core point detection algorithm based on multiple features derived from the fingerprint which are collectively used for consistent core point detection [52]. Here we use Orientation field, coherence, Poincare index for core point detection. Though all fingerprints don't possess core point still this algorithm is useful to detect high curvature regions and gives high accuracy as it combines advantages form individual features.

The next step in the development of fingerprint recognition systems is feature extraction and matching. We pass the pre-processed image as an input to this.

2.1.1.2 Fingerprint Matching Techniques

Automatic Fingerprint Identification Systems (AFIS) try to match fingerprint by matching these ridge valley structure. Mainly two types are systems are there [1], [29], they are Minutiae based matching and Correlation based matching. Fingerprint matching has been also approached from several different strategies, like image-based [53] and ridge pattern matching of fingerprint representations. There also exist graph-based schemes [54], [55], [56], [57], [58] for fingerprint matching. Minutiae based system try to identify the location and type of minutia and match it with database template. The accuracy is totally dependent on the identification of minutia point.

Due to the large number of possible translations, rotations, and scaling, aligning two minutiae point patterns is an extremely difficult problem. A number of algorithms have been proposed in the literature. A common technique for these algorithms is to use local features associated with minutiae and/or their spatial properties to reduce the exponential number of search paths.

Jain et al. [59], [60] use ridge information associated with minutiae as an aid for alignment. Minor modifications of this matching algorithm have been suggested by other researchers [61], [62], [63], [64]. Local structural features among several minutiae close to each other are used for alignment by reserachers [65], [66], [67], [68]. Chen et al. [61] defined a feature vector which describes the relationship between a minutia and its neighbors circled within a radius. Jiang and Yau [68] and Jea and Govindaraju [67] used features derived from minutia triplets. He et al. [66] built a minutia simplex that contains a pair of minutiae as well as their associated textures. These minutiae local feature representations may not be robust due to their reliance on the interdependency of minutiae, which can be missed or erroneously detected by a minutia extraction algorithm. The methods proposed by Hrechack [57], Wahab et al. [70], Kovács-Vajna [71], Germain et al. [72], as well as Tan [73] also use groups of minutiae to define local structural features. These local structural features are directly used for verification or identification, which is performed based on the pairs of corresponding local structures that are found between a query fingerprint and a template fingerprint or template fingerprint database. However, the local structural feature is less distinct because it is determined only by a small subset of the minutiae. Fingerprints from different fingers may have many similar local structures and fingerprints from the same finger may only have a few similar structures due to the presence of spurious minutiae and the absence of genuine minutiae. Therefore, fingerprint matching / identification based only on local structural features is less reliable.

In another approach information sampled around minutiae is used for alignment [74], [75], [76]. Tico and Kuosmannen [75] built a minutia descriptor for each minutia, which consists of the original minutia point and a set of ridge orientation information. Similar to the minutia descriptor, Qi et al. [74] defined a feature vector for each minutia by integration of ridge orientations. Tong et al. [76] proposed an adjacent feature vector which consists of four adjacent relative orientations and six ridge counts of a minutia. In contrast to the local structural features proposed in [64], [66], [67], and [68], the representations proposed in these methods are independent of any other minutia detected in the fingerprint. Hence, they could be more robust to the erroneous outcomes of the minutia detection algorithm (i.e., missing and spurious minutiae). Since core points of fingerprints are common, they can also be used as an aid for fingerprint alignment. Zhang [77] and Chan et al. [78] have explored this possibility. However, it is impossible to always guarantee locating the core point precisely, and sometimes the core point cannot be detected at all due to poor image quality or only a partial finger image being obtained via the sensor.

In case of correlation based techniques, rather than detecting minutiae, we go for global matching of ridge valley structure, here we try to match the texture of fingerprint. Such techniques are robust but less accurate. Recently, researchers have come up with hybrid fingerprint matchers by making use of more than one basic approach to matching. For example, Ross et al. [79] have suggested the use of both minutiae and ridge flow information to represent and match fingerprints. They have shown that the performance of the minutiae-based matcher presented them in earlier research [59] can be significantly improved by using additional information provided by the FingerCode method [47]. The correlation-based fingerprint matcher proposed by Bazen et al. [80] selects certain distinctive regions in the template fingerprint image and searches for those regions in the query image. However, their method is not very robust to rotation. The work of Beleznai et al. [81] attempts to exploit the structural information around minutiae to improve the recognition performance of a minutiae-based matcher. However, the focus of this work is the compression of the region around the minutia points using Principal Component Analysis (PCA) and Discrete Wavelet Transform to achieve a fast verification. Kovacs [71] proposed the use of small windows around the minutia to search for possible correspondences in the query image. Once the possible correspondences were found, the author used triangular matching to match the two fingerprints. Nandakumar & Jain have proposed a correlation based approach [82], they have presented local correlation-based fingerprint matching algorithm to improve the performance of a minutiae-based matcher by introducing a correlation step to ascertain the quality of each minutia match. The gray-level information of the pixels around the minutia points contains richer information about the local region than the attributes of the minutia points. Hence, the spatial correlation of regions around corresponding minutia points is a good measure of the degree of similarity between them. Next we discuss palmprint recognition systems.

2.1.2 Palmprint Recognition Systems

Palmprints are believed to have the critical properties of universality, uniqueness, permanence and collectability for personal authentication [1]. What's more, palmprints have some advantages over other hand-based biometric technologies, such as fingerprints and hand geometry. Palms are large in size and contain abundant features of different levels, such as creases, palm lines, texture, ridges, delta points and minutiae. Faking a palmprint is more difficult than faking a fingerprint because the palmprint texture is more complicated; and one seldom leaves his/her complete palmprint somewhere unintentionally.

As with fingerprint palmprint is also a multistage process. It consists of Palmprint Acquisition, Palmprint Enhancement, Feature Extraction & Matching.

2.1.2.1 Palmprint Acquisition

Generally palmprint images can be classified in two categories: offline and online. An offline palmprint can be acquired by samples inked on paper with almost up to 500 dpi resolution, and then it is transmitted into a computer through a digital scanner for later processing. The procedure is not suitable for real-time task and the hollowed central part of the palm is often missing [83], [84], [85]. Online palmprint can be obtained by CCD camera or digital scanner that is directly connected to a computer. The low resolution and real time processing make online palmprint recognition more popular nowadays [83], [84].

Pan et al. [83] & Othman et al. [86] have used a method where palmprint are obtained when users spread their hands on the scanner without any constraint of fixed pegs, which means image distortions such as rotation and shift are inevitably in the images. Peng & Dan [87] have used a scanner to create palm database. The palms in the database are captured by a device they designed. The key component was a digital camera Canon PowerShot A75, which has a 3.2 Megapixel CCD. The maximum resolution of this camera was 2048×1536. The captured image is then used for segmentation or Region of Interest (ROI) Extraction.

2.1.2.2 Palmprint Segmentation

The captured palmprint may be full palm or may a restricted palm area as discussed above, we have to extract the region of interest from it. This will be used for extracting feature vector for classification. We have proposed a segmentation algorithm based on Gabor filter & Otsu's Thresholding [45]. This will be applicable to separate the palm image from the background, and will be applicable for both the CCD camera and Scanned images.

Palmprint has center part which is rich in principal lines; we have to consistently locate a region (ROI) from this part. Many researchers are using a technique based on border tracing and locating extreme points [83], [86], [87], [88], [89], [90]. Pan & Ruan [83] have used border tracing and minima location to fit a co-ordinate system to palmprint. Gan & Zou have used similar approach of the partial template of palmprint [88].

2.1.2.3 Palmprint Feature Extraction & Matching

Palmprints are very rich in texture. We can form the feature vector by extracting texture information. Various approaches are followed by researchers. Pan & Ruan [83] used 2D Gabor filters at different angles to extract the feature information. A phase based palmprint matching approach is suggested by T. Aokit et al. [89]. They used a Band Pass phase only correlation method to extract the spectral information. Another correlation based method is presented by N. E. Othman et al. [86]. They proposed an approach based on the application of unconstrained minimum average correlation energy (UMACE) filter for palmprint feature extraction and representation [86]. The UMACE methodology determines a different filter for each palmprint of authentic class, the correlation function gives peak for authentic palmprint, and this property is used for classification.

Principal component analysis based approaches are suggested in [91], [92], [93], [94], [95]. They include PCA on PCA & 2D PCA analysis of Gabor Wavelets, Moment invariants etc. Wavelet energy based feature vector are also possible for palmprints [96]. K. Wong, G. Sainarayanan and A. Chekima [90] used wavelet energy of the palmprint ROI. Palmprint image was decomposed using different types of wavelets for six decomposition levels. Two different wavelet energy representations were tested. The feature vectors were compared to the database using Euclidean distance or classified using feed-forward back-propagation neural network.

X. Wu, K. Wang, D. Zhang [97] used 3 level decomposition of palmprint and formed the wavelet energy based feature vector for matching. We have proposed a feature based on wavelet energy entropy. We have used Kekre's Wavelet for extraction of feature vector and the palmprint was decomposed into five levels. For classification relative wavelet energy entropy as well as Euclidian distance based classifier is used [98].

2.1.3 Finger-knuckle Print Recognition Systems

Finger-knuckle-print (FKP) is one of emerging biometric traits, as scanner or capturing hardware for this has been developed and database for research purpose is available [99]. The finger-knuckle print (FKP) refers to the image of the outer surface of the finger phalangeal joint. FKP verification is a two-step process where first we locate the ROI and next feature extraction and matching is performed.

2.1.3.1 FKP Segmentation

The segmentation of ROI is actually developing a co-ordinate system and fitting it on to a Finger-knuckle print image. With such a co-ordinate system, an ROI can be segmented from the captured image for reliable feature extraction. Being new very few people have worked on this. Lin Zhang, Lei Zhang & D. Zhang [100] have proposed a co-ordinate fitting scheme based on convex coding. This coding scheme is applied on an edge map generated from canny edge detection of input FKP image. For all point we get a convex direction coding map. This was used to locate the FKP Region of interest (ROI). We have used another approach based on the grey scale gradient of the images [101]. We calculate the gradient orientation field and use it to locate the ROI. Next we discuss the existing matching techniques.

2.1.3.2 FKP Matching

The popularity & widespread use of hand-based biometrics should be attributed to its high user acceptance. In fact, the image pattern in the finger-knuckle surface is highly unique and thus can serve as a distinctive biometric identifier [99], [100]. FKP being recent has been yet to be thoroughly explored. The current research has shown great potential in FKP to be used as an efficient and accurate biometric trait [99], [100], [101], [102].

Hand geometry, especially 3D features from finger surface has been used by Woodard et al. [105], [106] as a biometric traits but specific localized part has not been proposed. They used curvature based shape index to represent the finger back surface, rather than texture rich Finger-knuckle surface.

Ravikanth & Kumar [107], [108] have proposed use of finger back surface as biometric feature; the whole back surface of hand is captured and then pre-processed to isolate the finger-knuckle. They used subspace analysis using PCA & LDA for FKP analysis, in [103] Zang et al. have discussed this as a sub-optimal approach for FKP verification. Band limited phase only correlation function is proposed in [104] by Zang et al. which give EER in the range of 5.5% to 0.31 %. In [102] they have proposed a local-global feature fusion for FKP verification; Local features are extracted using a bank of Gabor filters convolved with FKP ROI and global features are taken from band limited phase only correlation function. We have proposed use of wavelet based features [109], specifically wavelet energy of the FKP ROI for verification purpose. This is a faster approach attractive for online verification.

2.2 Face & Iris Recognition

2.2.1 Face Recognition

Among all biometrics listed above, face biometric is the biometric belonging to both physiological and behavioral categories. While the physiological part of the face biometric has been widely researched in the literature, the behavioral (related to emotions on face) part is not yet fully investigated. In addition, as reported in [1], [3], [4] face has advantage over other biometrics because it is a natural, non-intrusive, and easy-to-use biometric. For example [110], among the biometrics of face, finger, hand, voice, eye, DNA and signature, the face biometric ranks first in the compatibility evaluation of a machine readable travel document (MRTD)[110] system on the basis of six criteria: enrollment, renewal, machine assisted identity verification requirements, redundancy, public perception, and storage requirements and performance.

Being very popular and used for long time, a lot of research has been done in face recognition. Many face recognition methods have been proposed in the past few decades. A great number of methods are appearance based. Statistical techniques, such as PCA [111], LDA [112], ICA [113], and Bayes [114], etc., are used to extract low dimensional features from the intensity image directly for recognition. A major disadvantage of the appearance based approaches is that they are sensitive to lighting variation and expression changes since they require alignment of uniform-lighted image to take advantage of the correlation among different images. An elastic graph matching (EGM) method is recently developed [116] to alleviate these problems. The EGM method utilizes an attributed relational graph to characterize a face, with facial landmarks (fiducial points) as graph nodes, Gabor wavelet around each fiducial point as node attributes and distances between nodes as edge attributes. Wang & Tang [115] have integrated Bayesian algorithm and the Gabor to reduce intrapersonal variation.

Gabor filters are also widely used for extracting facial feature vectors. Zhang et al. [117] have used local Gabor binary patterns. They used a reduced set of local histograms based on Local Gabor Binary Patterns (LGBP). In the proposed method, a face image is first represented by the LGBP histograms which are extracted from the LGBP images. Then, the local LGBP histograms with high separability and low relevance are selected to obtain a dimension-reduced face descriptor. This method gave high reduction in dimensionality and about 94% accuracy. Gonzalez & Castro [118] have proposed another method based on Gabor filter which uses Shape driven Gabor Jets for face description and Authentication.

Arivazhagan, Mumtaj & Ganesan [119] used Multiresolution Transform such as, Gabor Wavelet Transform. Gabor Wavelet was used to extract the spatial frequency, spatial locality and orientation selectivity from faces irrespective of the variations in the expressions, illumination and pose & then Normalization was done. Then by considering each Eigen faces as each co-ordinate, a co-ordinate system was formed called Face space. In this Face space, each face was considered as a point. By projecting each faces its co-ordinate values were determined, which were later used for distance measures in discrimination analysis. Achieved accuracy varied from 84 to 94% on various databases considered.

Kotani and Quiu [120] have used vector quantization of face to generate a codevector histogram, the codebook is defined as a 33 different variation in grey levels. They generated a codevector histogram and matched them. This method is robust towards grey level intensity variations. Average recognition rate was 97%.

DCT was also used for face recognition by Ekenel Stiefelhagen [121], he utilized local information by using block-based discrete cosine transform (DCT). The main idea is to mitigate the effects of expression, illumination and occlusion variations by performing local analysis and by fusing the outputs of extracted local features at the feature and at the decision level. In this algorithm local information is extracted using block-based discrete cosine transform. Obtained local features are combined both at the feature level and at the decision level.

DCT has been used as a feature extraction step in various cases on face recognition. Up to now, either DCT features have been used in a holistic appearance-based sense [122], or local appearance-based sense which ignores spatial information during the classification step. Pan & Bolouri [123] used the DCT coefficients obtained from the image blocks are given as an input to a multi-layer perceptron, Sanderson & Paliwal [124] used the local DCT coefficients are modeled with GMM, Scott [125] proposed a network of networks (NoN) model which is fed by DCT coefficients and finally Kekre & Shah used Kekre’s transform coefficients of face for recognition purpose [126]. In another approach Kekre et al. [127] have proposed use of novel VQ algorithm. We have used Kekre’s Median Codebook Generation Algorithm (KMCG) for generating feature vector. The performance of the proposed method is compared with the well-known face recognition method based on Discrete Cosine Transform (DCT). From the results it is observed that our proposed method gives 92.67 % accuracy as compared to DCT. Further it is observed that KMCG requires 99.45% computation less than DCT. Another approach [128] is based on Wavelet Energy of face, we have used Kekre’s wavelet to generate energy based feature vector and compared performance with Haar wavelets. Next we discuss iris recognition techniques.

2.2.2 Iris Recognition

Generally, iris recognition system consists of four major steps. They include image acquisition from iris scanner, iris image preprocessing, feature extraction and enrollment / recognition.

Image acquisition is a very important process as iris image with bad quality will affect the entire iris recognition process. The iris is captured by specially designed high resolution cameras, user co-operation is also required. The captured iris image consists of whole eye. For recognition purpose we have to separate the circular iris part which contains information in texture. This is done in iris preprocessing steps.

2.2.2.1 Preprocessing

The iris image preprocessing step for mobile applications are more complicated as the iris images taken by the users are less controllable as in the controlled laboratory environment. Improper iris image preprocessing can also influence the subsequent processes like feature vector extraction and enrollment/recognition [129].

Consequently, the iris preprocessing step needs to be robust and perform iris localization accurately. Daugman [130] made use of integro-differential operators for iris localization. It searches the path circularly to detect the iris boundary. The system by Tisse et al. [131] implemented the integro-differential operators and Hough transform for iris localization. Wildes [132] implemented a gradient based edge detector (a generalized Hough transform) to detect local boundaries of an iris. Ma et al. [133] proposed a new algorithm which locates the center of pupil and uses it to approximate iris region before executing edge detection and Hough transform. Cui et al. [134] made use of the low frequency information from wavelet transform for pupil segmentation and localized the iris with integro-differential operator. Moreover, the eyelids detection was also performed after the eyelashes detection. These methods are used to define the area of iris which is later segmented for the feature extraction.

2.2.2.2 Iris Feature Extraction Methods

The iris texture contains information which should be extracted and represented using selected feature vector. S Attrachi & K Faez [135] have used a complex mapping procedure and best-fitting line for the iris segmentation and 1D Gabor filter with two dimensional Principal Component Analysis (2DPCA) for the recognition approach. In the recognition procedure, they used the real term of 1D Gabor filter. In order to reduce the dimensionality of the extracted features, the new introduced 2DPCA method was used. Another such system using Gabor filter, 2DPCA & Gabor Wavelet Neural Network (GWNN) was proposed by Zhou et al. [136].

Koh et al. have proposed multimodal iris recognition system [137] using two iris recognitions and also the levels of fusion and the integration strategies to improve overall system accuracy. This technique first implements the Daugman's iris system using the Gabor transform and Hamming distance. Second, they proposed an iris feature extraction method having a property of size invariant through the Fuzzy-LDA with five types of Contourlet transform. This gives a multimodal biometric system based on two iris recognition systems. To effectively integrate two systems, they used statistical distribution models based on matching values for genuine and impostor, respectively. Iris recognition based on linear discriminant analysis (LDA) and Linear Predictive Cepstral Coding (LPCC) was proposed by Chu & Ching [138]. In addition, a simple and fast training algorithm, particle swarm optimization (PSO), was also introduced for training the Probabilistic Neural Network (PNN)[138].

Paul & Monwar [139] proposed iris recognition system consists of an automatic segmentation system that is based on the Hough transform, and is able to localize the circular iris and pupil region, occluding eyelids and eyelashes, and reflections. The extracted iris region was then normalized into a rectangular block with constant dimensions to account for imaging inconsistencies. Finally, the phase data from 1D Log-Gabor filters was extracted and quantized to four levels to encode the unique pattern of the iris into a bit-wise biometric template.

Besides these approaches many other systems are proposed, we can see that the performance of the system greatly depends on preprocessing, localization & segmentation of the iris. We have developed a system which does not need the preprocessing. Transform based and VQ based approaches have been studied. We have tested full 2-dimensional Discrete Cosine Transform (DCT), full 2-dimensional Walsh Transform (WHT), and the proposed method DCT/WHT row mean and column mean [140]. Row mean DCT/WHT gives the best performance with the accuracy of 75.78% outperforming full 2-dimensional DCT/WHT with low accuracy around 66.10% further proposed Walsh Row/ Column mean requires 99.96% less computations as that of full 2-D DCT. Thus our proposed method not only gives better accuracy but also reduces computational time considerably. We have used Vector Quantization using Linde-Buzo-Gray (LBG) Algorithm, Kekre's Proportionate Error Algorithm (KPE) & Kekre's Fast Codebook Generation Algorithm (KFCG) for iris feature extraction [141], [142].

2.3 Handwritten Signature Recognition

Handwritten signature verification has been extensively studied & implemented. Its many applications include banking, credit card validation, security systems etc. In general, handwritten signature verification can be categorized into two kinds, on-line verification and off-line verification [1], [2], [3]. In On–line approach we can acquire more information about the signature which includes the dynamic properties of signature. We can extract information about the writing speed, pressure points, strokes, acceleration as well as the static characteristics of signatures [1], [143]. This leads to better accuracy because the dynamic characteristics are very difficult to imitate, but the system requires user co-operation and complex hardware. Digitizer tablets or pressure sensitive pads are used to scan signature dynamically [1]. In off–line signature recognition we are having the signature template coming from an imaging device, hence we have only static characteristic of the signatures. The person need not be present at the time of verification. Hence off-line signature verification is convenient in various situations like document verification, banking transactions etc. [1], [3], [144]. As we have a limited set of features for verification purpose, off-line signature recognition systems need to be designed very carefully to achieve the desired accuracy.

2.3.1 On-line Approach

On-line signature recognition considers the dynamic characteristics of signatures. Jain & Ross [145] have used critical points, speed curvature angle as features and they have reported FRR 2.8% and FAR 1.6 %. They used common as well as writer dependent thresholds but it was observed that the writer dependent thresholds give better accuracy.

Considering another approach Lei, Palla and Govindarajalu [146] have proposed a technique for finding correlation between two signature sequences for online recognition, they mapped the occurrence of different critical points on signature and the time scale and the correlation between these sequences was evaluated using a new parameter called Extended Regression Square (ER^2) coefficient the results were compared with an existing technique based on Dynamic Time Warping (DTW). They reported Equal Error rate (EER) 7.2% where the EER reported by DTW was 20.9 % with user dependent thresholds. Abdullah and Shoshan [147] used image invariant and dynamic features for On-Line signature recognition, they used the Fourier descriptors for invariance and writing speed was used as dynamic feature. Multi-layer perceptron neural network was used for classification.

Rhee and Cho [148] used Model guided segmentation approach for segment to segment comparison to obtain consistent segmentation. They used discriminative feature selection for skilled as well as random forgeries. They reported EER 3.4 %. Nalwa [149] used a moment and torque base approach for on-line signature recognition. His work is based parameterizing each on-line curve over its normalized arc length. These parameters are then represented along the length of the curve, in a moving coordinate frame. The measures of the curve within a sliding window that are analogous to the position of the center of mass, the torque exerted by a force, and the moments of inertia of a mass distribution about its center of mass. He recommended that each signature be represented by multiple models, these models, perhaps, local and global, shape based and dynamics based. The reported FRR was 7% and FAR was 1%.

Keit, Palanjppan used a pen pressure based method for online mode [150], they designed a system which used a specialized pen capable of sensing writing pressure of the person and then used the pressure signal for identification purpose. They have obtained FRR 2.13% and FAR 3.14%. Shafiei & Rabiee [151] have proposed a method based on variable length segmentation & Hidden Markov Model (HMM). J. hasna [152] have proposed a neural network based prototype for dynamic signature recognition, the system used method of verification by the Conjugate Gradient Neural Network (NN), and the FRR achieved was 1.6%.

We have proposed use of vector Quantization for signature recognition. We have used VQ algorithms like KFCG, KMCG for generating the codebook for the scanned signature [153]. A preprocessing method based on modified Digital Difference Analyzer (DDA) is also suggested by authors [154]. In another approach we have used feature vector generated by Gabor Filters & signatures pressure information [155]. This was a brief review of the on-line signature recognition. Next we consider the off-line approach for signature recognition.

2.3.2 Off-Line Signature Recognition

This is a convenient approach and various optimization techniques are applied to address the problem. Sabourin [156] used granulometric size distributions for the definition of local shape descriptors in an attempt to characterize the amount of signal activity exciting each retina on the focus of a superimposed grid. He then used a nearest neighbor and threshold-based classifier to detect random forgeries. A total error rate of 0.02% and 1.0% was reported for the respective classifiers.

Abbas [157] used a back propagation neural network prototype for the offline signature recognition. He used feed forward neural networks and three different training algorithms Vanilla, Enhanced and batch were used. A neuro-fuzzy system was proposed by Hanmandlu [158], they compared the angle made by the signature pixels are computed with respect to reference points and the angle distribution was then clustered with fuzzy c-means algorithm. Back propagation algorithm used for training neural network. The system reported FRR in the range of 5-16% with varying threshold.

Zhang [159] have proposed a Kernel Principal Component Self Regression (KPCSR) model for off-line signature verification and recognition problems. Developed from the Kernel Principal Component Regression (KPCR), the self-regression model selected a subset of the principal components from the kernel space for the input variables to accurately characterize each person’s signature, thus offering good verification and recognition performance. He reported FRR 92% and FAR 5%. Baltzakis [160] developed a neural network-based system for the detection of random forgeries. The system uses global features, grid features (pixel densities), and texture features (co-occurrence matrices) to represent each signature. For each one of these feature sets, a special two-stage perceptron one-class-one-network (OCON) classification structure is implemented. An average FRR and FAR of 3% and 9.8%, respectively was obtained. Armand, Blumenstein and Muthukkumarasamy [161] used combination of the Modified Direction Feature (MDF) in conjunction with additional distinguishing features to train and test two Neural Network-based classifiers. A resilient back propagation neural network and a Radial Basis Function neural network were compared. Using a publicly available database of 2106 signatures containing 936 genuine and 1170 forgeries, they obtained a verification rate of 91.12%.

Justino [162] used a discrete observation HMM to detect random, casual, and skilled forgeries. An FRR of 2.83% and an FAR of 1.44%, 2.50%, and 22.67% are reported for random, casual, and skilled forgeries, respectively. Kaewkongka, Chamnongthai and Thipakom [163] proposed a method of off-line signature recognition by using Hough transform to detect stroke lines from signature image. The Hough transform was used to extract the parameterized Hough space from signature skeleton as unique characteristic feature of signatures. Fang [164] developed a system that is based on the assumption that the cursive segments of forged signatures are generally less smooth than that of genuine ones. Two approaches are proposed to extract the smoothness feature: a crossing method and a fractal dimension method.

S. Audet, P. Bansal, and S. Baskaran [165], designed Off-line Signature Verification and Recognition using Support Vector Machine. They used global, directional and grid features of signatures. Support Vector Machine (SVM) was used to verify and classify the signatures and a classification ratio of 0.95 was obtained. Majhi, Reddy and Prasanna [166] proposed a morphological parameter for signature recognition, they proposed center of mass of signature segments, and the signature was split again and again at its center of mass to obtain a series of points in horizontal as well as vertical mode. The point sequence is then used as discriminating feature; the thresholds were selected separately for each person. They achieved FRR 14.58% and FAR 2.08%.

Kekre and Pinge used template matching approach [167]. The signature was segmented in predefined shape templates, in all 40 different templates were considered for feature extraction. They used neural network classifier. Two separate algorithms were used first algorithm used 40 shapes associated with each signature, neural network with 40 input nodes , 25 nodes in hidden layer and 10 nodes in output layer was used. The other algorithm used ratio vectors for all the signatures and all these vectors were used to train a neural network with 450 input nodes, 230 nodes in hidden layer and 10 nodes in output layer. Algorithm reported average FAR

10%. We have used cluster based features for signatures to develop multi-algorithmic signature recognition system [144]. Different features are combined to improve accuracy of final system. A morphological approach is also discussed, we evaluate the variation is signature pixels by calculating their locations in allowed variation bands [168].

We have discussed many significant biometric traits; next we discuss research on multimodal biometrics & fusion methodologies.

2.4 Multimodal Biometrics

Multimodal biometrics has emerged as a choice for secure authentication systems. Fall in the price of hardware and faster processing computers make multimodal biometrics an attractive option. Multimodal biometrics involves fusion of two or more biometric traits or algorithms. We discuss different combinations to form multimodal systems and fusion technologies.

2.4.1 Combinations of Biometric Traits

We have discussed different biometric traits like face, iris, fingerprints, palmprint, finger-knuckle print, static and dynamic signatures. We discuss different combinations of these traits to implement multimodal biometrics; they can be multimodal, multi-algorithmic, multi-sensor, multi-instance system as discussed previously.

Aguilar et al. have used fingerprints minutiae and statistical parameters [169] based on kurtosis and skewness of the thinned fingerprint ridge map. This is an example of multi-algorithmic system. In addition the parameters of more than one fingerprint were used for authentication. In another approach researchers have combined fingerprints with other modalities such as iris, face etc. C. Lupu [170] have proposed an hardware based system for car security, which combines fingerprint & iris features. Feten et al. [171] combined fingerprint minutiae feature with iris feature based on Gabor filters. The final decision of the system used the operator "AND" between decision coming from the fingerprint recognition step and that coming from the iris recognition one. Another such approach is proposed by A. Alpaslan [172], he used fingercode & iriscode feature extracted using tuned Gabor filters. Multilayered Artificial Neural Network (ANN) was used for classification, correct classification rates (CCR) up to 99.4% was achieved by this method.

Multimodal Biometric System based on Hand Geometry and Palm Print Texture is proposed by Ferrer et al. [177]. A Support Vector Machines was used as verifier. The palm print texture was obtained by means of a 2D Gabor phase encoding scheme. A robust co-ordinate system was defined to make easier image alignment. A Hamming distance and threshold are used for verifying the identity. A score and decision level fusion results have shown the improvement of the combined scheme. Chin et al. [178] proposed a multimodal biometrics system that combines fingerprint and palmprint. The quality of fingerprint and palmprint images are first enhanced using a series of preprocessing techniques. Following, a bank of 2D Gabor filters is used to independently extract fingerprint and palmprint features, which are then concatenated into a single feature vector. This approach gave EER 0.91%.

Combination of face and voice has been proposed by Jiang et al. [173]. The face was extracted from video feed. MFCC coefficients for voice data were used for classification. In the fusion step, features from both modalities are projected into nonlinear Laplacian Eigenmap subspace for multimodal speaker recognition and combined at low level. Ekenel et al. have developed a system based on face & voice, this concept was used for a smart room [174].

A multimodal biometric system based on face, ear and fingerprint [175] is proposed by Abate et al. They have analyzed the combination of the three different biometrics face, ear and fingerprint using both a new multimodal schema, namely the N-Cross Testing Protocol, and a fast hierarchical architecture. Achieved CCR was in the range of 94-98%. Pan et al. have fused face and ear features. They used Kernel Fisher discriminant analysis for the analysis [176]. The feature fusion algorithm based on KFDA is proposed and applied to multimodal recognition based on fusion of ear and profile face. With the algorithm, the fusion discriminant vectors of ear and profile face are established and nonlinear feature fusion projection could be implemented. The experimental results show that the method was efficient for feature-level fusion and the ear and face based multimodal recognition performs better than ear or profile face unimodal biometric recognition.

A multi sensor biometric system is one which uses different sensors for capturing the data. A multimodal biometrics system based on face appearance, shape and temperature is proposed by

Chang et al. [179]. This is a multi-modal face recognition using 2D, 3D and infrared images of the same set of subjects. Each sensor captures different aspects of human facial features; appearance in intensity representing surface reflectance from a light source, shape data representing depth values from the camera, and the pattern of heat emitted, respectively. The combination of 2D & 3D gives good classification accuracy; they reported accuracy in the range 90-98%. On the similar lines Chang, Bowyer and Flynn [180] have used PCA based feature extraction on 2D and 3D face recognition.

A Multimodal Iris Recognition Using Gabor Transform and Contourlet is discussed by H. Koh, W. Lee and M. Chun [181]. First, they implemented the Daugman's iris system using the Gabor transform and Hamming distance. Second, they proposed an iris feature extraction method having a property of size invariant through the Fuzzy-LDA with five types of Contourlet transform. Finally, they established a multimodal biometric system based on two iris recognition systems. To effectively aggregate two systems, they used statistical distribution models based on matching values for genuine and impostor, respectively. And then, they made comparisons of performance of the fusion algorithms such as weighted summation, Support Vector Machine, Fisher discriminant analysis, and Bayesian classifier.

T. Nakagawa et al. have proposed a multi-modal biometrics authentication using on-line signature and voice pitch [182]. They uses a self-correlation function for extraction of a voice pitch and verify by a standardized variable. Fusion methods of abstract level and score level were used for combining the modalities. Next we discuss some significant fusion strategies.

2.4.2 Fusion Techniques

It is generally known that a good fusion algorithm outperforms or at least performs as well as the individual classifiers. Considerable research in the pattern recognition field is focused on fusion rules that aggregate the outputs of the first level experts and make a final decision. Cheung, Mak & Kung have proposed a two level fusion strategy for audio-visual biometric authentication [183]. Specifically, fusion is performed at two levels: intramodal and intermodal. In intramodal fusion, the scores of multiple samples (e.g. utterances or video shots) obtained from the same modality are linearly combined, where the combination weights depend on the difference between the score values and a client-dependent reference score obtained during enrollment. This is followed by intermodal fusion in which the means of intramodal fused scores obtained from different modalities are either linearly combined or fused by a support vector machine (SVM). Experimental results show that intramodal and intermodal fusion are complementary to each other and that SVM-based intermodal fusion is superior to linear combination.

C. Barbu, R. Iqbal & J. Peng presented a novel information fusion approach that can be a very useful tool for multimodal biometrics learning [184]. The proposed technique is a multiple view generalization of AdaBoost in the sense that weak learners from various information sources are selected in each iteration based on lowest weighted error rate. Weak learners trained on individual views in each iteration rectify the bias introduced by learners in preceding iterations resulting in a self-regularizing behavior. They compared the classification performance of proposed technique with recent classifier fusion strategies in various domains such as face detection, gender classification and texture classification.

A score level fusion technique is proposed by S. Horng et al. [185]. They examined the performance of sum rule based score level fusion and Support Vector Machines (SVM) based score level fusion. Three biometric characteristics were considered in this study: fingerprint, face, and finger vein. They also proposed a new robust normalization scheme (Reduction of High scores Effect normalization) which is derived from min max normalization scheme. Experiments on four different multimodal databases suggest that integrating the proposed scheme in sum rule based fusion and SVM based fusion leads to consistently high accuracy.

Combination of Hyperbolic Functions for Multimodal Biometrics Data Fusion is suggested by Toh & Yau [186]. They proposed a network model to generate different combinations of the hyperbolic functions to achieve some approximation and classification properties. This is to circumvent the iterative training problem as seen in neural networks learning. In many decision data fusion applications, since individual classifiers or estimators to be combined would have attained a certain level of classification or approximation accuracy, this hyperbolic functions network can be used to combine these classifiers taking their decision outputs as the inputs to the network. The proposed hyperbolic functions network model was first applied to a function approximation problem to illustrate its approximation capability. The model was finally applied to combine the fingerprint and speaker verification decisions which show either better or comparable results with respect to several commonly used methods.

Feature fusion method based on Kernel Canonical Correlation Analysis (KCCA) is presented by X. Xu, Z. Mu [187] and applied to ear and profile face based multimodal biometrics for personal recognition. The fusion of ear and face biometrics could fully utilize their connection relationship of physiological location, and possess the advantage of recognizing people without their cooperation. First, the profile-view face images including ear part were used for recognition. Then the kernel trick was introduced to canonical correlation analysis (CCA), and the feature fusion method based on KCCA is established. With this method, a kind of nonlinear associated feature of ear and face was proposed for classification and recognition. The result of experiment shows that the method is efficient for feature fusion, and the multimodal recognition based on ear and profile face performs better than ear or profile face unimodal biometric recognition and enlarges the recognition range.

2.5 Summary

In this chapter we have reviewed various techniques of unimodal, multimodal biometric authentication. Sections 2.1 to section 2.3 have discussed individual biometric traits like fingerprint, palmprint, FKP, face & iris & handwritten signatures in detail. Section 2.4 is describing various techniques of combination of unimodal biometric traits to design multimodal biometric techniques. Various fusion mechanisms for combining and giving final decision for multimodal biometrics are discussed in section 2.4.2. Next we present our work based on different biometric traits.