CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter discusses some of the previous research works related to this research work. Previous works related to histogram equalization-based enhancement techniques are discussed in Section 2.3.1. Fuzzy-based enhancement techniques are discussed in Section 2.3.2. Section 2.3.3 discusses GA-based enhancement techniques. The techniques for palmprint recognition system and enhancement techniques used in palmprint recognition system are discussed in Section 2.3.4. A few histogram-based techniques are implemented for comparison purposes and are discussed in Section 2.4 in detail. Summary of the chapter is given in Section 2.5.

2.2 IMAGE ENHANCEMENT

The primary objective of image enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement is an important step in personal identification systems. Enhancement of the palmprint image before recognition will improve the performance of the system. There are many techniques available for image enhancement. Most of the work related to palmprint identification system uses histogram equalization as enhancement technique. But the traditional histogram equalization technique has various drawbacks. In order
to overcome those drawbacks, a suitable technique based on histogram equalization is needed.

2.3 CONTRAST ENHANCEMENT

Contrast (Burger and Burge 2008) is understood as a combination of the range of intensity values effectively used within a given image and the difference between the image’s maximum and minimum pixel values. In some digital images, the features of interest occupy only a relatively narrow range of the grayscale. One might use a point operation to expand the contrast of the features of interest so that they occupy a larger portion of the displayed gray-level range. This is known as contrast enhancement (Castleman 2007) or contrast stretching.

2.3.1 Histogram Equalization-Based Enhancement

The gray level histogram is a function showing the relationship between gray level and the number of pixels in the image with that gray level. It is a plot of gray level and its probability. The technique used for obtaining a uniform histogram is known as histogram linearization (Gonzalez and Woods 1999) or Histogram Equalization (HE).

Histogram equalization is a common technique for enhancing the appearance of images. Histogram equalization involves finding a gray scale transformation function that creates an output image with a uniform histogram (or nearly so). Suppose there is an image which is predominantly dark, then its histogram would be skewed towards the lower end of the gray scale and all the image details are compressed into the dark end of the histogram. If the gray levels are stretched at the dark end, they produce a more uniformly distributed histogram. The image would then be much clearer. Gray scale
transformation function can be determined assuming the gray levels to be continuous and normalized to lie between 0 and 1.

A transformation $T$ is found that maps gray values $r$ in the input image $F$ to gray values $s = T(r)$ in the transformed image. It is assumed that $T$ is single valued and monotonically increasing, and $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$ and the inverse transformation from $s$ to $r$ is given by $r = T^{-1}(s)$. If one takes the histogram for the input image and normalizes it, the area under the histogram is 1, having probability distribution for gray levels in the input image $P_r(r_k)$.

The probability distribution of gray levels in the input image is first calculated (Gonzalez and Woods 1999) as in Equation (2.1)

$$P_r(r_k) = \frac{n_k}{N}$$

where $n_k$ is the number of pixels having gray level $k$, and $N$ is the total number of pixels in the image. A plot of $P_r(r_k)$ versus $r_k$ is called as a histogram. The transformation is represented in Equation (2.2)

$$s_k = T(r_k) = \sum_{i=0}^{k} \frac{n_i}{N} = \sum_{i=0}^{k} P_r(r_k)$$

where $0 \leq r_k \leq 1$, the index $k = 0, 1, 2, \ldots, L-1$ and $0 \leq s_k \leq 1$. The values of $s_k$ will have to be scaled up by $L-1$ and rounded to the nearest integer so that the output values of this transformation will range from 0 to $L-1$. Thus the discretization and rounding of $s_k$ to the nearest integer will mean that the transformed image will not have a perfectly uniform histogram. Histogram equalization may not always produce desirable results, particularly if the given histogram is very narrow. It can produce false edges and regions. It can also increase image graininess and patchiness.
Rajavel (2010) introduced image independent brightness preserving histogram equalization for contrast enhancement and brightness preservation. It uses curvelet transform and histogram matching to enhance the image. Curvelet transform is used to identify bright regions of the image. Then the histogram of the original image is modified with respect to the histogram of the identified regions. This method does not preserve the brightness well. The computation complexity is also relatively high since it uses both curvelet and histogram matching techniques.

Lu et al (2009) presented a contrast enhancement technique based on Adaptively Increasing Value of Histogram Equalization (AIVHE). This method reshapes the original Probability Density Function (PDF) to obtain new PDF to prevent a significant change in the gray levels. It also provides a mechanism of adjustment to contrast enhancement by means of adaptive constraint parameter $\alpha_k$ for adjustment automatically, which is determined by the initial value $\gamma_k$ and user defined parameter $\beta_k$. Since it contains user defined parameter, human intervention is needed during the enhancement stage. Due to this fact, this method cannot be used in personal identification systems.

Arici et al (2009) introduced a contrast enhancement technique as an optimization problem that minimizes a cost function. This method is called Global Contrast Enhancement using Histogram Modification (GCE-HM). Here, the level of enhancement is adjusted by penalty terms. It incorporates noise robustness, black/white stretching and mean brightness preservation in the optimization module. This method improved only the visual quality of the image without considering the features in the image. Hence, it is suitable only in display applications.
Park et al (2008) presented a contrast enhancement method using dynamic range separate histogram equalization that separates the dynamic range of histogram into k parts and resizes the gray scale range based on its area ratio. Intensities of histogram are uniformly redistributed in resized gray scale range. Dynamic Range Separate Histogram Equalization (DRSHE) uses Weighted Average of Absolute colour Difference (WAAD) to emphasize the edge of original image and moderate the histogram variations effectively. Linear adaptive scale factor is used to reduce excessive changes in brightness. This method enhanced visual quality without highlighting details in the image. Hence, it is suitable only in display-oriented applications.

Kim and Chung (2008) introduced a recursively separated and weighted histogram equalization to enhance the image contrast as well as to preserve the image brightness. The essential idea of Recursively Separated and Weighted Histogram Equalization (RSWHE) is to segment an input histogram into two or more sub-histograms recursively, to modify the sub-histograms by means of a weighting process and to perform histogram equalization on the weighted sub-histograms independently. As the recursion level increases the enhancement decreases. This is a major drawback of RSWHE. RSIHE (Recursive Sub-Image Histogram Equalization) and RMSHE (Recursive Mean Separate Histogram Equalization) are some methods similar to RSWHE, but they do not carry out the above weighting process.

Sengee and Choi (2008) presented a Brightness Preserving Weight Clustering Histogram Equalization (BPWCHE) technique for image contrast enhancement. It simultaneously preserves the brightness of the original image and enhances visualization of the original image. BPWCHE assigns each non-zero bins of the original image histogram to a separate cluster and compute each cluster’s weight. Number of clusters is decided based on cluster weight,
weight ratio and widths of two neighbouring clusters. Transformation functions for each cluster’s sub-histogram are calculated based on the traditional HE method in the new acquired partitions of the result image histogram, and the sub histogram’s gray levels are mapped to the result image by the corresponding transfer functions. Histogram Equalization maps the gray level in the enhanced image through the transformation function that depends on the distribution of the gray level in the input image. BPWCH method improves the contrast but does not preserve the brightness well.

Sim et al (2007) described a recursive sub image HE for image contrast enhancement. RSIHE separates the histogram based on the median (gray level with cumulative probability density equal to 0.5). So, the total pixels in each sub image are same. The median-based histogram segmentation occurs many times recursively in RSIHE. This method produces $2^r$ pieces of sub histogram. Here, $r$ is recursion level and its value is set by the user. If the value of $r$ is larger, then the enhancement done is very less. This is the major problem in RSIHE.

Wang and Ward (2007) presented a fast image/video contrast enhancement based on Weighted Threshold Histogram Equalization (WTHE) for image contrast enhancement. It is a fast and effective method for image contrast enhancement based on weighted and thresholded HE. The PDF of an image is modified by weighting and thresholding before the HE is performed. That is, the original PDF value is replaced by a weighted and thresholded PDF value. It deals with the issue which provides a convenient and effective mechanism to control the enhancement process, while being adaptive to various types of images. WTHE enhancement method performs histogram equalization based on a modified histogram. This method does not preserve the brightness of the image. Artifacts are also present in the enhanced image.
Dynamic histogram equalization was presented by Wadud et al (2007) as a smart contrast enhancement technique based on conventional histogram equalization. Dynamic Histogram Equalization (DHE) technique takes control over the effect of traditional one so that it performs the enhancement of an image without making any loss of details in it. DHE objective is to eliminate the domination of higher histogram components on lower histogram components in the image histogram and to control the amount of stretching of gray levels for reasonable enhancement of the image features. This method divides the input histogram into a number of sub-histograms based on local minima until it ensures that no dominating portion is present in any of the newly created sub-histograms. Then, a dynamic gray level range is allocated for each sub-histogram based on their dynamic range in the input image and cumulative distribution of histogram values. This allotment of stretching range of contrast prevents small features of the input image from being dominated and washed out. It ensures a moderate contrast enhancement of each portion of the whole image. Finally for each sub-histogram, a separate transformation function is calculated based on the traditional HE method, and gray levels of input image are mapped to the output image accordingly. DHE does not put any constraint on maintaining the mean brightness of the image. Thus, this method is not suitable in personal identification systems as saturation effect may occur.

Brightness Preserving Dynamic Histogram Equalization (BPDHE) was introduced by Ibrahim and Kong (2007) for image contrast enhancement and brightness preservation. It is an extension to HE. This method smoothes the input histogram with one-dimensional Gaussian filter, and then partitions the smoothed histogram based on its local maximums. Next, each partition will be assigned to a new dynamic range. After that, the histogram equalization process is applied independently to these partitions based on this new dynamic range. The changes in dynamic range and also histogram
equalization process will alter the mean brightness of the image. Finally, the output image is normalized to the input mean brightness. It uses Average Absolute Mean Brightness Error (AAMBE) as a measure for brightness preservation. This method preserves the brightness well but contrast is not improved.

Brightness Preserving Histogram Equalization with Maximum Entropy (BPHEME) was introduced by Wang and Ye (2005) for image contrast enhancement and brightness preservation. It uses a variation approach to find the optimal histogram, which has the maximum differential entropy under the mean brightness preservation constraint, and then implements the histogram specification under the instruction of that desired histogram. Thus an optimal brightness preserving enhancement method using histogram transformation is used to maximize the target histogram’s entropy under the constraints of brightness. The input image has the gray levels in a small interval, and the output image is to stretch the gray levels in a larger interval. Thus they have the same discrete entropy. However, the output is obviously enhanced due to its larger dynamic range than the input. AMBE, Mean Absolute Mean Brightness Error (MAMBE) and Entropy are used as the metrics for evaluating this method. This method introduces discretization error and non-cleavability of the histogram line.

In order to overcome the drawbacks of the traditional HE methods, the Bin Underflow and Bin Overflow (BUBO) method was presented by Yang et al (2003) for image contrast enhancement. It puts constraint on the PDF with the bin underflow and bin overflow thresholds to prevent a significant change of gray levels. This method cannot expand gray-level distribution to expand dynamic range of the input image. This is the major drawback of this method. To expand dynamic range of image, the method still needs adjustment of different parameter for input images.
RMSHE method was introduced by Chen and Ramli (2003) for image contrast enhancement. RMSHE performs the separation recursively based on the mean of the image. In typical HE, no mean separation is performed and thus, brightness preservation is not done. In Brightness Preserving Bi-Histogram Equalization (BBHE) the mean-separation is done once and thus, certain extent of brightness preservation is achieved. HE is equivalent to RMSHE with recursion level, \( r = 0 \). BBHE is equivalent to RMSHE with recursion level \( r = 1 \). When \( r = 0 \), no decomposition occurs. This case is simply equivalent to conventional histogram equalization. When \( r = 1 \), the input histogram \( H(X) \) is decomposed into two sub-histograms \( H_L(X) \) and \( H_U(X) \) based on the input mean \( X_M \). Obviously, this case is the same as BBHE. When \( r = 2 \), \( H_L(X) \) is divided further into \( H_{LL}(X) \) and \( H_{LU}(X) \) based on a new mean \( X_{ML} \). \( H_U(X) \) is also divided further into \( H_{UL}(X) \) and \( H_{UU}(X) \) based on another new mean \( X_{MU} \). Here, \( X_{ML} \) is the mean of the sub-histogram \( H_L(X) \), whereas \( X_{MU} \) is the mean of the sub-histogram \( H_U(X) \). Similar procedures can be carried out when \( r \) is greater than 2. As the recursion level \( r \) increases, the mean of the output image come near to the input mean \( X_M \). This is the drawback of RMSHE method.

Chen and Ramli (2003a) presented a Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) method for image contrast enhancement and brightness preservation. Using the input mean as the threshold level to separate the histogram does not guarantee maximum brightness preservation. The brightness preservation in MMBEBHE is based on an objective measurement referred to as AMBE. It is defined as the absolute difference between the input and the output mean. Lower AMBE implies better brightness preservation. Here, the threshold level is chosen based on the resulting AMBE and not fixed to the input mean. In MMBEBHE, first AMBE is calculated for each of the threshold levels. Then the threshold level, \( X_T \) that yields minimum mean brightness error is found.
Finally, the input histogram is separated into two sub histograms based on the $X_T$ and equalized independently. This method causes more annoying side effects depending on the variation of gray level distribution in the histogram.

Wan et al (1999) presented Dualistic Sub Image Histogram Equalization (DSIHE) for image contrast enhancement. This method separates the histogram based on gray level with cumulative probability density equal to 0.5 instead of the mean. The input histogram $H(X)$ is decomposed into two sub-histograms $H_L(X)$ and $H_U(X)$ based on the input median $X_D$. Then each of $H_L(X)$ and $H_U(X)$ is then equalized independently. The theory behind is that this would yield maximum entropy for the output image, also it does not present a significant shift in relation to the brightness of the input image, especially for the large area of the image with the same gray-levels (represented by small areas in histograms with great concentration of gray-levels) e.g., images with small objects regarding to great darker or brighter backgrounds. This method preserves the brightness to some extent only since the separation takes place only once.

The BBHE was presented by Kim (1997) for image contrast enhancement and brightness preservation. BBHE firstly decomposes an input image into two sub images based on the mean of the input image. One of the sub images is the set of samples less than or equal to the mean, whereas the other one is the set of samples greater than the mean. Then the BBHE equalizes the sub images independently based on their respective histograms with the constraint that the samples in the formal set are mapped into the range from the minimum gray level to the input mean and the samples in the latter set are mapped into the range from the mean to the maximum gray level. BBHE set the threshold level, $X_T$ as input mean which does not guarantee minimum AMBE.
Quantized Bi-histogram Equalization (QBHE) was introduced by Kim (1997a) for image contrast enhancement. It is a simplified version of the bi-histogram equalization. QBHE separates the input histogram into two sections. These two histogram sections are then equalized independently. The major difference among the methods in this family is the criteria used to divide the input histogram. QBHE uses the average intensity value as their separating point. The essence of the bi-histogram equalization is to utilize independent histogram equalizations separately over two sub images obtained by decomposing the input image based on its mean. QBHE is an extension of a typical histogram equalization, which utilizes Cumulative Density Function (CDF) of a quantized image and performs independent histogram equalizations over two sub images obtained by decomposing the input image based on its mean. This method does not preserve the brightness well and artifacts are present in the enhanced image.

2.3.2 Fuzzy-Based Image Enhancement

Verma et al (2012) presented a high dynamic range optimal fuzzy color image enhancement using artificial ant colony system based on fuzzy logic and modified artificial ant colony system. The lower and the upper thresholds are defined to provide an estimate of the underexposed, mixed-exposed and overexposed regions in the image. The Red, Green and Blue (RGB) color space is converted into Hue, Saturation and Value (HSV) color space so as to preserve the chromatic information. Gaussian Member Functions (MF) suitable for the underexposed and overexposed regions of the image are used for the fuzzification. Parametric sigmoid functions are used for enhancing the luminance components of under and over-exposed regions. Mixed-exposed regions are left untouched throughout the process. An objective function comprising of Shannon entropy function as the information factor and visual appeal indicator is optimized using artificial ant colony
system to ascertain the parameters needed for the enhancement of a particular image. Visual appeal is preferred over the consideration of entropy so as to make the image human-eye-friendly. In this method, visual appearance is given more importance than enhancement of features in the image. Hence, this method is less suitable to personal identification system. Moreover, this method does not eliminate the saturation effect completely.

Image improvement using modern fuzzy algorithm based on genetic algorithm calculation was introduced by Nejad et al (2011) for image enhancement in fuzzy domain. Due to uncertainties in concepts, fuzzy idea is used in this method. In this approach, a new scale of parameter modern is introduced which is based on Sujeno supplementary parameter. The applied transmission function parameters are obtained using genetic algorithm with the purpose of maximizing the scale. The computation complexity of this method is high and it does not achieve better performance.

Jayaram et al (2011) presented a fuzzy inference system-based contrast enhancement method for image contrast enhancement. Here, a method of generating the fuzzy if then rules specific to a given image based on the local information is given. A partial histogram is generated to save the computational costs. The enhanced image contains artifacts and this method does not preserve the mean brightness.

Fuzzy-based filtering approach on histogram specification for fingerprint image enhancement was given by Perumal et al (2011) for image contrast enhancement. It uses fuzzy histogram technique. In this, a fuzzy modeling approach is described which is used for reducing the noise and increasing the brightness of the ridges. This method does not give better enhancement and it does not preserve the mean brightness.
Kundra et al (2009) presented an image enhancement method based on fuzzy logic. It performs fuzzy-based impulse noise removal. This method used Fuzzy Inference System (FIS) which helps to take the decision about the pixels of the image under consideration. This method focused on the removal of the impulse noise with the preservation of edge sharpness and image details along with improving the contrast of the images. A window size of $3 \times 3$ is used. Gradient values are calculated in all eight directions. Fuzzy gradient value is calculated using the fuzzy rules. Membership function is derived from these values. Using the membership function, the image is transformed to fuzzy domain. Noise removal is done in the fuzzy domain. Finally, the image is brought back to the original domain. This output image is then enhanced using another membership function. Here, noise removal is done in the first phase and contrast enhancement is done in the second phase. The enhanced image of this method contains artifacts.

Wang and Ruan (2008) introduced palmprint image enhancement using steerable filters-based fuzzy unsharp masking. Palm lines include principal lines and wrinkles, which can uniquely describe an individual palmprint. Here, the motive of palmprint image enhancement is to highlight palm lines. This method introduced the fuzzy set theory into the unsharp masking scheme. Moreover in this method, a highpass filter is replaced with steerable filters in unsharp masking scheme. In order to further enhance the contrast of wrinkles, a half open membership function is used to transform the output of steerable filters into fuzzy domain. The steerable filter is used to get the high frequency components of the original image. The output of the steerable filter is transformed to fuzzy domain using a half open membership function. After fuzzification, the image is normalized. Image enhancement is performed in the fuzzy domain. Finally, the enhanced image is mapped into gray levels. The enhanced image contains unwanted artifacts, and fine line features are lost during the enhancement process.
Maode et al (2007) presented an adaptive fuzzy image enhancement algorithm for local regions. In order to deal with the drawbacks of low speed and losing image information in fuzzy image enhancement algorithms, a fuzzy enhancement operator with close-character and transplantable-character is used in this approach. The approached operator employed the gradient operator to make the image enhancement processing focus on the interested regions, and the otsu operator to automatically select the best threshold value, which can realize an adaptive fuzzy image enhancement algorithm for local regions. The enhanced image contains unwanted artifacts and noise.

An improved unsharp masking method is described by Wang and Ruan (2006) to enhance the palmprint image. The motive of palmprint image enhancement is to highlight the fine details of palm lines. In this method, a fuzzy unsharp masking algorithm is used to enhance the contrast of a palmprint image. This method introduces the fuzzy set theory into the unsharp masking scheme. Unsharp Masking (UM) approaches are simple and effective for contrast enhancement of high-frequency components. Most of UM algorithms can effectively improve the contrast of principal lines, but are insensitive to wrinkles. In order to further enhance the contrast of wrinkles, a half open membership function is used to transform the output of the filters into fuzzy domain. Here, the Laplacian filter is used to get the high frequency component of the original image. Weiner filter is used to restrict sharpening in smooth areas. Using a half open membership function, the Weiner filtered image is transformed to fuzzy domain. Because the wrinkle lines are thinner and shallower than principal lines, the contrast of wrinkles is lower than that of the principal lines in the original palmprint image. To sharpen much more wrinkles than principal lines, the first task is to distinguish wrinkles, principal lines and background. However, it is difficult to use conventional set theory to represent the degree in which a pixel belongs to a wrinkle, a principal line or background, because they are fuzzy. To highlight the wrinkles, a half open
fuzzy membership function is defined to fuzzificate the Wiener filter output. The parameters of the membership function directly affect the result of fuzzification. The parameters depend on the mean and variance of the Wiener filter output. The output is then normalized and enhancement is done in the fuzzy domain. Finally, the enhanced image in the fuzzy field is mapped to gray levels. The enhanced image contains unwanted artifacts, and fine line features are lost during the enhancement process.

Farbiz et al (2000) introduced a new fuzzy logic filter for image enhancement. The fuzzy logic control-based filter has the ability to remove impulsive noise and smooth Gaussian noise. It also preserves edges and image details efficiently. To achieve these three image enhancement goals, first filters that have excellent edge-preserving capability are developed. Next, the filters are modified so that they perform all three image enhancement tasks. These filters are based on the idea that individual pixels should not be uniformly fired by each of the fuzzy rules. This filter is called as Sharpening and Smoothing Fuzzy Control Filter (SSFCF). The enhanced image still contains noise and the contrast is not improved well.

Cheng and Xu (2000) presented a fuzzy logic approach to image contrast enhancement. Here, an adaptive direct fuzzy contrast enhancement method is used based on the fuzzy entropy principle and fuzzy set theory. First, histogram of the input image is calculated. Then, local maxima of the histogram are found. Average height of the local maxima is calculated and a local maximum as a peak is selected if its height is greater than the average height. The first peak and the last peak are selected. Two gray levels are selected based on information loss criteria. The two parameters are calculated from this available data and another parameter is calculated based on the maximum fuzzy entropy principle. A membership function is constructed using these parameters. Sobel operator is used for each pixel according to the
membership value. The mean edge value is also calculated. Contrast is calculated in relation to the membership value. Enhanced contrast is then calculated. With this enhanced contrast, membership value is modified. Finally, modified membership value is mapped to new gray level. Even though this method improves the contrast, noise is still present in the enhanced image and it does not preserve the mean brightness.

Choi and krishnapuram (1997) introduced a robust approach to image enhancement based on fuzzy logic. This method performed image enhancement using fuzzy rules. Its goals are removing impulse noise, smoothing out nonimpulse noise and enhancing (or preserving) edges and certain other salient structures. Three different filters are derived for each of the above three tasks using the weighted (or fuzzy) least squares method, and the criteria for selecting each of the three filters are defined. The criteria are based on the local context, and they constitute the antecedent clauses of the fuzzy rules. The overall result of the fuzzy rule-based system is the combination of the results of the individual filters, where each result contributes to the degree that the corresponding antecedent clause is satisfied. The contaminated images were constructed by adding zero-mean Gaussian noise and a small percentage of impulse noise to the original images. Here, the impulse noise is generated by two different methods. The first one is by replacing a certain percent of the pixels by black or white pixels with equal probability and the other is by Gaussian impulse noise. The three different filtering systems are the filtering system for removing impulse noise, the filtering system for edge preserving smoothing and the filtering system for detail preserving smoothing. They were applied to these contaminated images. A window of size 5× 5 is used for filters. The enhanced image contains unwanted artifacts and is blurred to some extent.
Bhandari et al (1993) presented an image enhancement method incorporating fuzzy fitness function in genetic algorithms. Genetic algorithm represents a class of highly parallel adaptive search processes for solving a wide range of optimization and machine learning problems. This method uses effectiveness of searching global optimal solution in selecting an appropriate image enhancement operator automatically. Here, the initial population is generated. Then the fitness function is evaluated. Genetic operators are used during reproduction to bring the best child. With the newly generated child, fitness function is evaluated and this process is repeated until optimum solution is obtained. Finally, the algorithm provides the best value of the parameter based on the fitness value. The enhanced image contains unwanted artifacts.

2.3.3 Genetic Algorithm-Based Image Enhancement

Zhang et al (2010) presented an image enhancement technique using genetic algorithm and non-linear gain operation in undecimated wavelet domain for typhoon cloud image. Noise in a typhoon cloud image is reduced by modifying the undecimated wavelet coefficients by combining with Generalized Cross Validation (GCV) at fine resolution levels. GA and non-linear gain operation are used to modify the undecimated wavelet coefficients at coarse resolution levels in order to extrude the details of a typhoon cloud image. Information entropy, contrast measure and PSNR are used as quality measures. The computation complexity of this method is high and the enhanced image contains unwanted artifacts.

Hashemi et al (2010) introduced an image contrast enhancement method based on genetic algorithm. It uses a simple and novel chromosome representation together with corresponding operators. This method gave natural-looking images especially when the dynamic range of the input image is high. This method used a simple chromosome structure. Initial population
is generated through a random or user-specified process. The number of edges and their overall intensity are used as fitness value. Terminating criteria is a condition that is used for ending the GA procedure. Here, termination is based on the difference of best fitness in two last consecutive generations. The contrast of the enhanced image is low and visual quality of the image is not improved.

An automated GA-based fuzzy image enhancement method was presented by Khayat et al (2009) for image enhancement. Here, a Parametric Indices of Fuzziness (PIF) are introduced, which server as the optimization criterion of the contrast enhancement procedure. The PIF comprises of Sugeno class of involutive fuzzy complements and the first order fuzzy moments of the image. The PIF as the measure of fuzziness is maximized, and the maximum of PIF is tuned based on the first-order moment of the image. The parameters of the transformation function are found by the genetic algorithm aiming to maximize the PIF. This method does not preserve the mean brightness of the image.

Zhang and Wang (2009) introduced a typhoon cloud image enhancement algorithm for reducing speckle with genetic algorithm in stationary wavelet domain. It uses discrete Stationary Wavelet Transform (SWT), GCV, GA, and non-linear gain operator. An efficient de-noising and enhancement algorithm for typhoon cloud image is given. Noise in a typhoon cloud image is reduced by modifying the stationary wavelet coefficients using GA and GCV at fine resolution levels. Asymptotical optimal de-noising threshold is obtained, without knowing the variance of noise, by only employing the known input image data. GA and non-linear gain operator are used to modify the stationary wavelet coefficients at coarse resolution levels in order to enhance the details of a typhoon cloud image. In order to accurately assess an enhanced typhoon cloud image’s quality, an overall score
index is used based on information entropy, contrast measure and PSNR. The enhanced image still contains unwanted artifacts and computation complexity of this method is high.

Universal impulse noise filter based on genetic programming was presented by Petrovic and Crnojevic (2008) for removal of noise from an image. It is based on the switching scheme with two cascaded detectors and two corresponding estimators. Genetic programming as a supervised learning algorithm is employed for building two detectors with complementary characteristics. The first detector identifies the majority of noisy pixels. The second detector searches for the remaining noise missed by the first detectors which are usually hidden in image details or having amplitudes close to its local neighborhood. Both detectors are based on the robust estimators of location and scale, i.e. median and Median Absolute Deviation (MAD). This method does not provide satisfactory results for images with more noise. As the noise level increases, the performance decreases.

Paulinas and Usinskas (2007) presented a survey of genetic algorithms applications for image enhancement and segmentation. It showed that genetic algorithms are the most powerful unbiased optimization techniques for sampling a large solution space. Because of unbiased stochastic sampling, they are quickly adapted in image processing. They are applied for the image enhancement, segmentation, feature extraction and classification as well as the image generation. It gave a brief overview of the canonical genetic algorithm and it also reviews the tasks of image preprocessing. As the field of genetic algorithms applications is growing fast, the constant improvement of genetic algorithms will definitely help to solve various complex image processing tasks.

Munteanu and Rosa (2000) introduced an automatic image enhancement technique based on real-coded GA. The task of the GA is to
adapt the parameters of a novel extension to a local enhancement technique similar to statistical scaling, and to enhance the contrast and detail in the image according to an objective fitness criterion. This method is computationally complex and does not preserve the mean brightness.

2.3.4 Palmprint Recognition-Based System

Xuan et al (2012) described a texture-based algorithm for palmprint recognition combining Two Dimensional (2D) Gabor wavelets and Pulse Coupled Neural Network (PCNN) which can be applied in criminal detection, personal identification and user authentication. Here, palmprint images are decomposed by 2D Gabor wavelets, and then PCNN is employed to imitate the creatural vision perceptive process and decompose each Gabor subband into a series of binary images. Entropies for these binary images are calculated and regarded as features. A support vector machine-based classifier is employed to implement classification. This method obtained a classification accuracy of 97.37%. This method does not employ any technique for image enhancement.

In contrast with Three Dimensional (3D) and geometry technology (Li et al 2011), there are more unique features for palmprint that can be used for personal identification. As a result, a better performance and user acceptance is ensured. When the demand of highly accurate and robust palmprint authentication system is increased, researchers developed a new approach called multispectral imaging (Zhang et al 2010) that can be used for obtaining more discriminative information and so the antispoof capability of palmprint is also improved. For high-security applications (e.g., forensic usage), this method provides less accuracy. It is because high-resolution palmprints (500 ppi or higher) are required from which more useful information is extracted (Dai and Shou 2011).
Zuo et al (2011) investigated the accurate orientation extraction and appropriate distance measure problems for effective palmprint recognition using steerable filter. First, high order steerable filter is used to extract accurate continuous orientation and quantify it into discrete representation. Then, for effective matching of accurate orientations, a generalized orientation distance measure is used. This distance measure is also used for matching of discrete orientations. Experiments are carried on both Hong Kong Polytechnic University and Chinese Academy of Science Institute of Automation (CASIA) palmprint databases.

Badrinath and Gupta (2011) presented a technique to extract palmprint features based on instantaneous-phase difference obtained using Stockwell transform of overlapping circular-strips. The hand images are acquired using a low cost scanner. A procedure is used to classify hand images into either right or left hand based on their inherent characteristics, and then the palmprint region from the hand image is extracted accordingly. This palmprint region is found to be robust to translation and rotation on the scanner. The extracted palmprint is enhanced using histogram equalization method. This system is tested on Indian Institute of Technology Kanpur (IITK) database, CASIA database and Hong Kong Polytechnic University database.

Zhang et al (2010) presented a personal authentication system that simultaneously exploits 2D and 3D palmprint features. The objective of this work is to improve accuracy and robustness of existing palmprint authentication systems using 3D palmprint features. This multilevel framework for personal authentication efficiently utilizes the robustness (against spoof attacks) of the 3D features and the high discriminating power of the 2D features. This system used an active stereo technique and structured light, to simultaneously capture 3D image or range data and a registered
intensity image of the palm. The surface curvature feature-based method is investigated for 3D palmprint feature extraction while Gabor feature-based competitive coding scheme is used for 2D representation. These representations for their individual performance is compared with multilevel matcher that utilizes fixed score level combination scheme to integrate information. This method does not include enhancement in the preprocessing stage and its performance is tested with only moderate sized database.

Michael et al (2010) presented an innovative contactless palmprint and knuckle print recognition system for personal identification. It uses palmprint and knuckle print tracking approach to automatically detect and capture these features from low-resolution video stream. A simple directional coding technique is used to encode the palmprint feature in bit string representation. The bit string representation offers speedy template matching and enables more effective template storage and retrieval. A scheme to extract knuckleprint feature via ridgelet transform is also described. The scores output by the palmprint and knuckleprint experts are fused using Support Vector Machine (SVM). This system works satisfactorily in semi-controlled environments. It is not tested in open environments. The system database contains only moderate number of users.

Chen and Kegl (2010) introduced an invariant pattern recognition system using contourlets and AdaBoost. It described methods for palmprint classification and handwritten numeral recognition using the contourlet features. The contourlet transform is a two dimensional extension of the wavelet transform using multiscale and directional filter banks. AdaBoost is used as a classifier in this experiment. The contourlet features are very stable features for invariant palmprint classification and handwritten numeral recognition. This method does not perform image enhancement before feature extraction process.
Punsawad and Wongsawat (2009) introduced palmprint image enhancement using phase congruency. It uses the phase congruency feature to enhance the palmprint. It detects the edges in palmprint image. Here, phase congruency is used as a tool for detecting lines and edges in the palmprint image. This method needs adjustment of different parameters for different conditions of image. This is the major drawback of this method. Moreover, the line features are not clearly visible in the enhanced image.

Yue et al (2009) presented a competitive coding scheme-based system for palmprint recognition. It first convolves the palmprint image with a bank of Gabor filters with different orientations and then encodes the dominant orientation into its bitwise representation. Based on the statistical orientation distribution and the orientation separation characteristics, a modified fuzzy C-means cluster algorithm is used to determine the orientation of each Gabor filter. It is observed that improved competitive code with six filters would be a preferable choice for palmprint recognition. This method uses Gaussian filter and morphological operators for preprocessing the palmprint image. Morphological operators affect the shape of structures in the palmprint image. Implementation becomes difficult when structuring element is large.

Pan and Ruan (2009) introduced a palmprint recognition system using Gabor-based local invariant features. It extracts local invariant features using Gabor function, to handle the variations of rotation, translation and illumination, raised by the capturing device and the palm structure. The local invariant features were obtained by dividing a Gabor-filtered image into two-layered partitions and then calculating the differences of variance between each lower-layer sub-block and their resided upper-layer block (called local relative variance). The extracted features only reflect relations between local
sub-blocks and its resided upper-layer block, so that the global disturbance occurred on palmprint images is counteracted.

Nanni and Lumini (2009) presented image-based fingerprint matchers for personal identification. It focused on the use of image-based techniques in fingerprint verification. This work compared the several texture-based descriptors for fingerprints and gave a novel image-based fingerprint matcher based on the minutiae alignment. Here, the feature extraction is performed locally on a decomposition of the fingerprint in several overlapping sub-windows considering the following measures: Gabor filters descriptors, invariant local binary patterns and histogram of gradients. Moreover, a supervised selection of a small subset of descriptors is performed, in order to reduce the dimensionality of the feature set discarding the less discriminative features. This method is not robust to noise.

Pan and Ruan (2008) introduced a palmprint recognition system with improved two-dimensional locality preserving projections. The Improved Two-Dimensional Locality Preserving Projections (I2DLPP) mainly focuses on two aspects. Firstly, the nearest-neighbor graph is constructed in which each node corresponds to a column inside the matrix instead of the whole image. Secondly, Two Dimensional Principal Component Analysis (2DPCA) is implemented in the row direction prior to Two Dimensional Locality Preserving Projections (2DLPP) in the column direction to reduce the calculation complexity and the final feature dimensions.

Nanni and Lumini (2008) presented a hybrid fingerprint matcher based on local binary patterns. The two fingerprints to be matched are first aligned using their minutiae, then the images are decomposed in several overlapping sub-windows. Then, each sub-window is convolved with a bank of Gabor filters. Finally, the invariant local binary pattern histograms are
extracted from the convolved images. Computational complexity of this method is high due to windowing process.

Leung et al (2007) presented a palmprint verification system for controlling access to shared computing resources. It uses $3 \times 3$ averaging mask to remove noise and make line extraction more accurate. Blurring effect is seen in the enhanced palmprint image. Yang et al (2007) presented an information fusion of biometrics based on fingerprint, hand-geometry and palmprint for personal identification. It enhanced the input image by means of local histogram equalization. Local histogram equalization creates blocking effect (discontinuity problem) near boundaries of the sub blocks. It uses only local information inside each block without considering the intensity balance of the whole image.

Badrinath and Gupta (2007) introduced an efficient multi-algorithmic fusion system based on palmprint for personal identification. It applied morphological operations to remove any isolated small blobs or holes. Morphological operators change the shape of structures in the palmprint. Choras (2007) presented a human identification system based on biometrics. It used histogram equalization for contrast enhancement. Traditional HE method introduces artifacts in the enhanced image and it does not preserve the mean brightness of the image.

Chen et al (2007) introduced a biometric verification system by fusing hand geometry and palmprint. It performed histogram equalization to enhance the ROI image of palmprint. But the traditional HE technique has the problem of mean shift and saturation effect. Zheng et al (2007) presented a paper on offline palmprint image enhancement. It applied orientation filters for noise removal. This filter does not perform well for higher noise level. Blurring effect is seen in the enhanced palmprint images. Multispectral whole-hand biometric authentication system is presented by Rowe et al.
Kumar et al (2007) introduced discretization of hand-geometry features, using the entropy-based heuristics to achieve the performance improvement. The performance improvement due to the unsupervised and supervised discretization schemes is compared with a variety of classifiers like k-NN (Nearest Neighbor) and SVM.

Hennings et al (2007) presented a palmprint classification algorithm with the use of multiple correlation filters. Correlation filters are classifiers that produce a sharp peak when filtering a sample of their class and a noisy output for other classes. For every class, the filters are trained for a palm at different locations, where the palmprint region has a high degree of line content. With the use of a line detection procedure and a simple line energy measure, any region of the palm can be scored and the top-ranked regions are used to train the filters for each class. Extraction of line features and palmprint points as well as feature extraction using Principal Component Analysis (PCA) and linear discriminant analysis have been addressed using medium-size databases of palmprint images. Most of the research performed on palmprint recognition uses palmprint images captured from a digital camera. Here palmprint recognition is performed by using images from the PolyU database.

Wang et al (2007) introduced a fingerprint matching using orientation codes and polylines. This method extracts two novel discriminative features that describe three kinds of information, namely macro orientation patterns, micro ridge representation and minutiae of fingerprints. Orientation codes and polylines features are in fixed-length. They are measured in similarity and effective in various stages of fingerprint matching,
such as alignment, minutiae pairing, matching score computation and matching rates fusion.

Nanni and Lumini (2007) presented a hybrid wavelet-based fingerprint matcher based on the multi-resolution analysis of the fingerprint pattern and on minutiae-based registration module. Two fingerprints are first aligned using their minutiae, then the images are divided into sub-windows and each subwindow is decomposed into frequency sub-bands at different decomposition levels using a set of wavelet functions. Finally, a distinct classifier is trained on each sub-band to distinguish matching pairs of fingerprint from the non-matching ones (defining a two-class matching problem). The features extracted for the matching are the result of standard deviation of the image convolved with 16 Gabor filters. The selection among the pool of matchers is performed by running sequential forward floating selection. The retained matchers are weighted by a novel localized quality measure and combined by a fusion rule.

Gan and Zhoul (2006) presented a palmprint recognition system based on wavelet transform. This method has done enhancement using gray level mapping algorithm. Gray level mapping algorithm introduces unwanted artifacts in the enhanced image. This method has the mean shift problem. So, it does not preserve the mean brightness. Kumar and Zhang (2006) presented a personal recognition system using hand shape and texture. This method applied morphological operations to remove any isolated small blobs or holes. Morphological operators affect the shape of structures of the palmprint image.

Wu and Qiu (2006) presented a hierarchical palmprint identification method using hand geometry and grayscale distribution features. This method performed preprocessing before authentication. Image is denoised with mid value filter, and histogram equalization is done to improve the contrast. Mid value filter creates blur effect in the enhanced
image and HE introduces unwanted artifacts in the enhanced image. Due to this problem, the performance of the system will be affected.

Lu et al (2006) introduced a palmprint recognition system using wavelet decomposition and 2D principal component analysis. This method performed image denoising and histogram equalization during the preprocessing stage. In order to improve the performance and to overcome the drawback of traditional HE technique, other HE-based technique can be used. Arif et al (2006) presented a personal identification system using hand feature. This method employed preprocessing with a morphological filter to fill in all small gaps and blacken the isolated white pixels. Morphological operators affect the shape of structures in the palmprint. In order to overcome this drawback, other denoising techniques can be used.

Shang et al (2006) introduced a method for recognizing palmprint based on Radial Basis Probabilistic Neural Network (RBPNN). The RBPNN is trained by the Orthogonal Least Square (OLS) algorithm and its structure is optimized by the recursive OLS algorithm. Palmprint is pre-processed by a Fast fixed-point algorithm for Independent Component Analysis (FastICA). A fast fixed-point algorithm for independent component analysis (FastICA) to extract features of palmprint images is given.

Kong et al (2006) introduced a feature-level fusion approach for improving the efficiency of palmprint identification. Multiple elliptical Gabor filters with different orientations are employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the fusion code. The similarity of two fusion codes is measured by their normalized hamming distance. A dynamic threshold is used for the final decisions.
Wu et al (2006) presented a novel approach for palm line extraction and matching for the use in personal authentication system. To extract palm lines, a set of directional line detectors are devised, and then these detectors are used to extract the lines in different directions. To avoid losing the details of the palm line structure, these irregular lines are represented using their chain code. To match palm lines, a matching score is defined between two palm prints according to the points of their palm lines. This method does not perform enhancement before the line extraction process.

Liu and Zhang (2005) introduced a wide line detector using an isotropic nonlinear filter for palmprint recognition. Lines provide important information in images, and line detection is crucial in many applications. Line detection plays an important role for the success of higher level processing such as matching and recognition. A nonlinear filter is used to extract a line completely without any derivative. The detector is based on the isotropic responses via circular masks. A general scheme for the analysis of the robustness of the wide line detector is introduced and the dynamic selection of parameters is developed. In addition, it investigated the relationship between the size of circular masks and the width of detected lines. This method also did not incorporate enhancement in the recognition system. The presence of noise in the palmprint images will affect the performance of the recognition system.

Kumar and Zhang (2005) introduced a palmprint authentication system based on multiple palmprint representation. Depending on the selected representation, the performance of the authentication system will vary. Use of a single palmprint representation has become the bottleneck in producing high performance. Three major palmprint representations are Gabor, line and appearance- based. Performance of authentication will increase using the combined features of these representations. It produces better results
compared to using each representation separately. An ideal palmprint-based personal authentication system should be able to reliably discriminate individuals using all of the available information. This authentication system used a combination of three major representations of palmprint. A fixed combination rule based on product of sum rule is used in this work.

Ribaric and Fratic (2005) presented a multimodal biometric identification system based on the features of the human hand. It described a biometric approach to personal identification using eigenfinger and eigenpalm features, with fusion applied at the matching-score level. The identification process is done by capturing the image, pre-processing, extracting and normalizing the palm and strip-like finger subimages. Eigenpalm and eigenfinger features are extracted based on the K-L transform. After the extraction, matching is done. Then the matcher’s outputs were normalized and fusion at the matching-score level is obtained by means of the total similarity measure. Finally, a decision is taken based on the modified k-NN classifier and thresholding.

Ribaric and Fratic (2005a) presented a biometrics verification system based on the fusion of palmprint and face features. This method used enhancement in the preprocessing step. Gaussian smoothing and contrast enhancement are done during the preprocessing step. Blurring effect is seen in the enhanced image and contrast is not improved.

Noh and Rhee (2005) introduced a palmprint identification algorithm using hu invariant moments and ostu binarization. This method performed histogram equalization for palmprint enhancement. Doi and Yamanaka (2005) presented a personal authentication system based on discrete finger and palmar feature extraction method. This method made noise reduction using a binary noise removal algorithm with repetitive
morphological operations of erosions and dilations in the preprocessing stage. It also used a directional enhancing filter for the crease detection.

Pang et al (2005) presented a palmprint authentication system with zernike moments. This method used traditional histogram-based method for palmprint enhancement. It emphasized on image enhancement which is a crucial and necessary part before feature extraction. Enhancement is done with traditional HE algorithm. But the traditional HE method has the mean shift problem. It introduces unnatural artifacts in the enhanced image. Similarly, the morphological operators affect the shape of structures in the palmprint. Hence, a more sophisticated enhancement technique is needed for palmprint enhancement.

Kumar and Shen (2004) presented a palmprint identification system using palmcodes. An approach for the palmprint identification using Real Gabor Function (RGF) filtering is investigated. Inkless composite hand images have been used to automatically extract the palmprints from peg-free imaging setup. These palmprints, after normalization, are subjected to selective feature sampling by a bank of RGF. Each of these filtered images has been used to extract significant features (PalmCode) from each of the six concentric circular bands. Scale invariance problem is not considered in this method.

Zhang and Zhang (2004) presented a palmprint classification system based on wavelet signatures via directional context modeling. The palmprint is first transformed into the wavelet domain, and the directional context of each wavelet subband is defined and computed in order to collect the predominant coefficients of its principal lines and wrinkles. A set of statistical signatures, which includes gravity center, density, spatial dispersivity and energy, is then defined to characterize the palmprint with the selected directional context values. This method uses only global signature.
Hence, signature of some palmprints may be very similar. This method is tested with small database. Hence, reliability is less.

Kumar and Zhang (2004) introduced a palmprint authentication system using multiple classifiers. It investigated the performance improvement for palmprint authentication using multiple classifiers. Personal authentication using palmprints can be divided into three categories, namely appearance, line, and texture-based. A combination of these approaches is used to achieve higher performance. Palmprint features from PCA, line detectors and Gabor-filters are simultaneously extracted and combined with their corresponding matching scores.

Kumar and Zhang (2004a) presented a hand verification system by integrating shape and texture feature. This method investigated the performance of a bimodal biometric system using fusion of shape and texture. Several new hand-shape features are included to improve the performance for hand-shape based user authentication. Here, image is processed with morphological operations to remove any isolated small blobs or holes. Discrete Cosine Transform (DCT) coefficients are used for palmprint authentication. The score level fusion of hand shape and palmprint features uses product rule. Morphological operators create blurred image and their performance is not well when noise level is high.

Wu et al (2004) introduced an algorithm to classify the low resolution palmprints. Palmprints are classified by taking their most visible and stable features, that is principal lines. First the principal lines of the palm are defined using their position and thickness. Most palmprints show three principal lines, heart line, head line and life line. The principal lines are extracted by using directional line detectors in terms of their characteristics. The line initials of the principal lines are extracted based on these line initials and a recursive process is applied to extract the principal lines in their
entirety. Finally, palmprints are classified into six categories according to the number of the principal lines and the number of their intersections. This method did not include enhancement algorithm for line extraction. Fingerprint identification (Maltoni et al 2003) has progressed over many years, but it cannot be used in a small part of the population due to age, accidents, genetic reasons, environmental or occupational reasons.

Han et al (2003) introduced a personal authentication using palmprint features. It is a verification approach using the biological features inherent in each individual. They are processed based on the identical, portable and arduous duplicate characteristics. Here, a scanner-based personal authentication system using the palmprint features is done. It is very suitable in many network-based applications. The authentication system consists of enrollment and verification stages. In the enrollment stage, the training samples are collected and processed by pre-processing, feature extraction and modeling modules to generate the matching templates. In the verification stage, a query sample is also processed by the pre-processing and feature extraction modules, and then is matched with the reference templates to decide whether it is a genuine sample or not. The ROI for each sample is first obtained from the preprocessing module. Then, the palmprint features are extracted from the ROI using Sobel and morphological operations. The reference templates for a specific user are generated in the modeling module. Finally, template-matching is done and the backpropagation neural network is used to measure the similarity in the verification stage.

Lu et al (2003) presented a palmprint recognition system using eigenpalms features. By means of the Karhunen–Loeve transform, the original palmprint images are transformed into a small set of feature space, called eigenpalms, which are the eigenvectors of the training set and can represent the principle components of the palmprints quite well. Then, the
eigenpalm features are applied to palmprint recognition with a Euclidean distance classifier.

Zhang et al (2003) introduced a new biometric approach for online personal identification using palmprint technology. An on-line system captures palmprint images using a palmprint capture sensor that is directly connected to a computer for real-time processing. Online palmprint identification system employs low-resolution palmprint images to achieve effective personal identification. The system consists of two parts, a device for online palmprint image acquisition and an efficient algorithm for fast palmprint recognition. A robust image coordinate system is defined to facilitate image alignment for feature extraction. In addition, a 2D Gabor phase encoding scheme is used for palmprint feature extraction and representation. Experiments are not conducted with noisy images and speed of the system needs to be improved.

Fisherpalms based palmprint recognition is described by Wu et al (2003) for personal recognition. In this method, each pixel of a palmprint image is considered as a coordinate in a high-dimensional image space. A linear projection based on fisher linear discriminant is used to project palmprints from this high dimensional original palmprint space to a significantly lower dimensional feature space (Fisherpalm space), in which the palmprints from the different palms can be discriminated much more efficiently. The relationship between the recognition accuracy and the resolution of the palmprint image is also investigated.

Kong et al (2003) presented a palmprint recognition system using 2D Gabor filters. A 2D Gabor filter is used to obtain texture information and two palmprint images are compared in terms of their hamming distance. Decision-level fusion in fingerprint verification (Prabhakar and Jain 2002) utilized classifier combination at decision level which stresses the importance
of classifier selection during combination. This scheme is optimal when sufficient data are available to obtain reasonable estimates of the joint densities of classifier outputs. Four different fingerprint matching algorithms are combined using this scheme to improve the accuracy of a fingerprint verification system.

A feature extraction method by converting a palmprint image from a spatial domain to a frequency domain using Fourier transform is given by Li et al. (2002). The identification process involves preprocessing, feature extraction, feature matching and decision-making. The features extracted in the frequency domain are used as indexes to the palmprint templates in the database and the searching process for the best match is conducted in a layered fashion. This performance of the method is not good.

Jain et al. (1999) presented a prototype hand geometry based identity authentication system for personal identification. Geometric measurements of the human hand have been used for identity authentication in a number of commercial systems. This verification system used the geometry of a person's hand to authenticate the identity. A technique for computing the various features (invariant to the lighting conditions of the device, presence of noise and the color of the skin) is described. A prototype image acquisition system was developed to capture the profile of the hand.

Zhang and Shu (1999) presented a palmprint verification system using datum point invariance and line feature matching. This method performed automatic personal identification using two characteristics, namely datum point invariance and line feature matching. The datum points of palmprint which have the remarkable advantage of invariable location are defined. They are determined using the directional projection algorithm. Then, line feature extraction and line matching are done to detect whether a
couple of palmprints are from the same palm. The performance achieved by this method is not good.

Funada et al (1998) introduced a feature extraction method for palmprint considering elimination of creases. Palmprint images have many creases which are organized like ridges. Owing to this, ordinary fingerprint feature extraction algorithms are unable to extract ridges. This method extracted ridges under these conditions. At first, the original palmprint image is divided into local images. The ridge candidates are extracted from each local image of the palmprint. Finally, only one candidate is selected as the ridge in the local image by estimating the continuity of certain properties. Although iris (Daugman 1994) and retinal recognitions provide optimum accuracy, the high costs of input devices or intrusion into users prevent the use of this method.

2.4 EXISTING ENHANCEMENT TECHNIQUES IMPLEMENTED IN THIS WORK

Some of the existing HE-based techniques like BUBO, WTHE, AIVHE, GCE-HM are implemented for comparing with the proposed techniques. The detailed descriptions of these techniques are given in this section.

2.4.1 Bin Underflow and Bin Overflow Method

The BUBO method puts constraint on the PDF with the bin underflow and bin overflow thresholds to prevent a significant change of gray levels Yang et al (2003). The PDF of BUBO method is represented in Equation (2.3)
\[ P_{BUBO}(k) = \begin{cases} C_{BO}, & \text{if } P(k) > C_{BO} \\ P(k), & \text{if } C_{BU} \geq P(k) \leq C_{BO} \\ C_{BU}, & \text{if } P(k) < C_{BU} \end{cases} \]  

(2.3)

where \( C_{BU} \) and \( C_{BO} \) are calculated as in Equation (2.4)

\[
\begin{align*}
C_{BU} &= \frac{(1 - b)}{N} \\
C_{BO} &= \frac{(1 + b)}{N}
\end{align*}
\]  

(2.4)

where \( b \) varies from 0 to infinity, and \( N \) is the total number of pixels in the given input image. This method cannot expand grey-level distribution to expand dynamic range of input image. To expand dynamic range of image, the method still needs adjustment of different parameters for input images.

2.4.2 Weighted Threshold Histogram Equalization Method

WTHE enhancement method performs histogram equalization based on a modified histogram. The original PDF value is replaced by a weighted and thresholded PDF value.

The increment in the output gray level \( H_k \) is represented in Equation (2.5)

\[
\Delta H_k = (L-1) \times P_{wt}(k)
\]  

(2.5)

where \( \Delta H_k \) is the increment in the output gray level \( H_k \)

\( P_{wt}(k) \) is obtained by applying a transformation function \( TR(k) \) to \( P(k) \). It is given in Equation (2.6)

\[
P_{wt}(k) = TR(P(k))
\]  

(2.6)
The transformation function $\text{TR}(P(k))$ is given in Equation (2.7)

$$
\text{TR}(P(k)) =
\begin{cases} 
  \frac{P_u}{P_u - P_l} \times P_u & \text{if } P(k) > P_u \\
  \frac{P(k) - P_l}{P_u - P_l}^r & \text{if } P_l \leq P(k) \leq P_u \\
  0 & \text{if } P(k) < P_l
\end{cases}
$$

(2.7)

The original PDF is clamped at an upper threshold $P_u$ and a lower threshold $P_l$, and all values between the upper and lower thresholds are transformed using a normalized power law function with index $r > 0$.

The increment for each intensity level is decided by the transformed histogram. The index $r$ of the power law function controls the level increment. For example, with $r < 1$, the power law function gives higher weights to the low probabilities in the PDF than the high probabilities. Therefore, with $r < 1$, the less-probable levels are protected and level saturation is less likely to occur. In the WTHE method, $r$ is the most important parameter through which the degree of enhancement is controlled.

Besides the weighting mechanism described above, the PDF is also thresholded at an upper limit $P_u$. As a result, all levels with probabilities higher than $P_u$ will have their increments clamped at a maximum value $\Delta_{\text{max}} = (L-1) \cdot P_u$ (as per Equation 2.6 and 2.7). This further avoids the dominance of the high-probability levels in the output dynamic range. The value of $P_u$ is decided by the formula given in Equation (2.8)

$$
P_u = v \times P_{\text{max}}, \quad 0 < v \leq 1
$$

(2.8)

where $P_{\text{max}}$ is the peak value (highest probability value) of the original PDF. The real number $v$ defines the upper threshold, normalized to $P_{\text{max}}$. It can be seen from Equation (2.7) that when $r=1$, $P_u=1$ and $P_l=0$ the WTHE method reduces to the original HE. Some other global HE-based methods, such as the
BUBO method, can also be considered special cases of the WT HE method. For a large variety of images, the value of $v$ can be kept constant while achieving satisfactory effect of enhancement. After obtaining the weighted thresholded PDF $P_{\text{wt}}(k)$, the equalization process is similar to the traditional HE. The CDF is obtained by Equation (2.9)

$$C_{\text{wt}}(k) = \sum_{m=0}^{k} P_{\text{wt}}(m), \text{for } k=0,1,\ldots,L-1$$  \hspace{1cm} (2.9)

and HE procedure is then performed as in Equation (2.10)

$$G(i,j) = W_{\text{out}} \times C_{\text{wt}}(F(i,j)) + M_{\text{adj}}$$  \hspace{1cm} (2.10)

where $W_{\text{out}}$ is the dynamic range of the output image. $M_{\text{adj}}$ is the mean adjustment factor that compensates for the mean change after enhancement. For a simple case, $W_{\text{out}}$ is equal to the full range $[0, L-1]$, and $M_{\text{adj}}=0$. $F(i,j)$ is the original image and $G(i,j)$ is the enhanced image.

$$W_{\text{out}} = \min (L-1,G_{\text{max}} \cdot W_{\text{in}})$$ in which $W_{\text{in}}$ is the dynamic range of the input image and $G_{\text{max}}$ is a pre-set maximum gain of dynamic range. $G_{\text{max}}$ is set in the range of 1.5 to 3.0. $M_{\text{adj}}$ is decided by calculating the mean of the enhanced image $F(i,j)$ assuming $M_{\text{adj}}=0$. Then the difference between the mean of the original and enhanced image is calculated. $M_{\text{adj}}$ is set to a value closest to the above mean difference that does not cause serious level saturation.

### 2.4.3 Adaptively Increasing Value of Histogram Equalization Method

AIVHE method reshapes the original PDF to obtain new PDF to prevent a significant change in the gray levels. It also provides a mechanism of adjustment to contrast enhancement by means of adaptive constraint
parameter $\alpha_s(k)$, which is determined by the initial value $\gamma_s$ and user defined parameter $\beta_s$. AIVHE divides the original PDF into upper and lower blocks on the basis of $P_{bas}$. A value of maximum threshold $P_h$ is set to restrict the variation of the $P_{AIVHE}(k)$, and then the value of $P_{AIVHE}(k)$ is limited to not greater than $P_h$. AIVHE reshapes original PDF and obtain the $P_{AIVHE}(k)$ using Equation (2.11).

$$P_{AIVHE}(k) = \begin{cases} P_h, & \text{if } P(k) \geq P_h \\ P(k) - \alpha_s(k)(P(k) - P_{bas}) \times \beta_x, & \text{if } P_{bas} < P(k) < P_h \\ P(k) \times \alpha_s k(P_{bas} - P(k)) \times \beta_x, & \text{if } P(k) \leq P_{bas} \end{cases}$$

$$\text{(2.11)}$$

where $P_{bas}$ is set to the average PDF, $P_h$ is set as double of $P_{bas}$, $\beta_s$ is used to adjust the enhancement effect by user, and $\alpha_s(k)$ is the adaptive constraint parameter for adjustment automatically. The initial value for $\beta_s$ is a real number in the range of [0,1]. The function of HE is produced when $\beta_s$ is set to zero and $P_{bas}$ is the mean value of the maximum and minimum value of $P(k)$. Dark and bright regions stretching is controlled by $\gamma_s$ at $\alpha_s(k)$. Whole contrast enhancement effect of the image is controlled by $\beta_s$. The effective constraint parameter can be calculated as in Equation (2.12)

$$\alpha_s(k) = \begin{cases} (1-(X_m-k)/X_m)^2 \times (1-\gamma_s) + \gamma_s, & \text{if } k \leq X_m \\ (1-(k-X_m)/(L-1-X_m))^2 \times (1-\gamma_s) + \gamma_s, & \text{if } k > X_m \end{cases}$$

$$\text{(2.12)}$$
where, $X_m$ is the mean brightness and $\gamma_x$ is a real number in the range of $[0, 1]$. Using $P_{AIVHE}(k)$, the cumulative density function, $C_{AIVHE}(k)$, is calculated. $C_{AIVHE}(k)$ is normalized to gray level $[0, L-1]$ and then the output image is obtained as in Equation (2.13)

$$F(k) = (L-1) \times \frac{C_{AIVHE}(k)}{C_{AIVHE}(L-1)}$$

(2.13)

where $F(k)$ is the input/output transfer function, $L-1$ is the maximum gray level, $k$ is the $k^{th}$ gray level and $C_{AIVHE}(k)$ is the CDF.

2.4.4  Global Contrast Enhancement using Histogram Modification Method

This method uses three concepts for contrast enhancement. They are histogram smoothing, black and white stretching and weighted histogram approximation. The algorithm for this method is given below.

Input: Input image $f$,

- B & W stretch parameters: $b$, $w$, and $1/(1+\zeta_y)$,
- Level of Enhancement $g$,

Output: Modified Histogram $\hat{h}$

Steps:
- Initialize $k$
- for each row $m$ do
  - for each column $n$ do
    - $k = k + |f[m,n] - f[m,n-2]|$
    - if $|f[m,n] - f[m,n-2]| > $Threshold then
      - $++ h_i[f[m,n]]$

Normalize $g_k$ to get $k^*$

$u = \min\{\text{count}/256, u_{\min}\}$

for each bin $n$ do

if $b < n < w$, then

$$h[n] = (1-k^*)u + k* h_i[n]$$

else

$$h[n] = 1/(1+\alpha_y)(1-k^*)u + k* h_i[n]$$

end

end

The modified histogram is then equalized by the HE technique.

2.5 SUMMARY

Most of the work discussed in the chapter tries to improve the performance of the palmprint recognition system by adding more features or applying different techniques to extract palmprint features. Only few works have been done in palmprint enhancement. Incorporating enhancement techniques in the preprocessing stage will improve the system performance. Hence, new techniques for palmprint enhancement are needed. This work focuses on developing new techniques for palmprint enhancement.