Histogram Gabor Phase Pattern and Adaptive Binning Technique in Feature Selection for Face Verification

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Abstract

The aim of this paper is to develop a robust system for face recognition by using Histogram Gabor Phase Pattern (HGPP) and adaptive binning technique. Gabor wavelet function is used for representing the features of the image both in frequency and orientation level. The huge feature space created by Gabor wavelet is classified by using adaptive binning technique. The unused bin spaces are used. As a result of which, the size of the space is drastically reduced and high quality HGPP created. It is due to this approach, the computation complexity and the time taken for the process is reduced and the recognition rate of the face improved. The significance of this system is its compatibility in yielding best results in the face recognition with major factors of a face image. The system is verified with FERET database and the results are compared with those of the existing methods.

Keywords: Face Recognition, Gabor Wavelets, Local Gabor Phase pattern, Global Gabor Phase Pattern, Adaptive Binning, and Spatial Histograms.

1. INTRODUCTION

Face recognition, the most coveted field in Image Processing, is still in its initial stages. It is due to its scientific challenges and potential applications, Face recognition has been an active research topic over the past few years. The Gabor wavelets approach appears to be quite perspective and it has several advantages such as invariance to some degree with respect to homogenous illumination changes, small changes in head poise, robustness against facial hair, and image noise [1,2]. Experimental results show that the proposed method performs better than traditional approaches in terms of both efficiency and accuracy.

To eliminate extrinsic factors, various feature extraction and selection methods are used. One such a method is HGPP. In this method, the quadrant bit codes are first extracted from face based on the Gabor transformation and Histogram techniques. The features of HGPP lie in two aspects. They are: i) HGPP can describe the general face images robustly without training procedure, ii) Encodes the Gabor phase Information, instead of Gabor magnitude information. This method uses two Gabor Phase Patterns (GPP's) to encode the phase variations which use high dimensional histogram features resulting in performance decrease and computational complexity. In this proposed system, the above stated problems are rectified by using adaptive binning method. As a result, the overall efficiency of the face recognition system is increased.

1.1. Challenges Associated With Face Verification

Face verification and recognition is a challenging problem due to variations in pose, illumination, and expression. So, Techniques that can provide effective feature representation with enhanced discriminability are crucial [3]. Face recognition has become one of the most active research areas and it plays an important role in many applications such as human machine interaction, authentication, and surveillance. However, the wide range variations of human face due to pose, illumination, and expression not only result in a highly complex distribution but also deteriorate the verification rate. It seems impractical to collect sufficient prototype images covering all the possible variations. Therefore, it is highly imperative in research to construct a small size training face verifier which is robust to environmental variations.

2. EXPERIMENTS

2.1. Block Diagram

The Figure 1 shows the entire block design of the proposed system with new methodology.

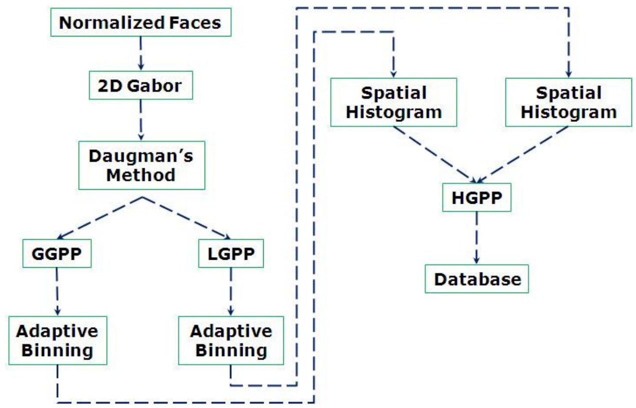

FIGURE 1: Block design for the proposed system

The Normalized face is given as input to the four different processes i) gabor filters ii) daugman's method, iii) Global Gabor Phase Pattern (GGPP) and iv) Local Gabor Phase Pattern (LGPP). For the Adaptive binning, the result obtained from GGPP and LGPP is given as input. This method works by creating a bin of size 3x3. And the resultant value obtained from adaptive binning is given to Spatial Histogram and the outputs of spatial histogram are used to create HGPP. Using HGPP value for the test image and trained dataset the relevant matched images are obtained.

Adaptive binning is a method for binning images according to the local count rate. It attempts to adaptively bin a single image, based on the number of pixels in each region. The basic method is to bin pixels in two dimensions by a factor of two, until the fractional Poisson error of the count in each bin becomes less than or equal to a threshold value. When the error is below this value, those pixels are not binned any further. The algorithm starts with the smallest possible bin size of 1×1 pixel and then calculates the average mean count for each bin. Each bin with an average mean count higher than the threshold value is marked as binned and its pixel members are removed from the pixel list, and ignored during the rest of the binning process. In the next iteration, the unbinned pixels are rebinned with square bins of double the side length. This process is repeated until all pixels are binned or the bin size exceeds the image size. Adaptive Binning of image feature is done, since the number of features obtained after the GGP operations is large. In order to reduce the number of features and at the same time to retain meaningful information adaptive binning is performed.

2.2. Gabor Wavelets

Gabor feature has been recognized as one of the best representations for face recognition. Traditionally, only the magnitudes of the Gabor coefficients are thought to be valuable for face recognition, and the phases of Gabor features are deemed to be useless and always discarded directly by almost all researchers in face recognition community [4, 5]. When The spatial histograms generated by encoding Gabor phases through Local Binary Pattern (LBP) they yield better recognition rate comparable with that of Gabor magnitude based methods. And it is also shown that the Gabor phases are quite compensatory to the magnitude information, since higher classification accuracy is achieved by combining Gabor phases and magnitudes. All these observations suggest that more attention should be paid to Gabor phases for face recognition. Among various wavelet bases, Gabor functions provide the optimized resolution both in the spatial and frequency domains.

2.3. Gabor Wavelets Functions

Gabor wavelet are obtained by using eq-1

$$\Psi_{u,v}(z) = \frac{(\|K_{u,v}\|)^2}{\sigma^2} e^{\frac{(-\|K_{u,v}\|\|z\|)^2}{2\sigma^2}} \left[e^{iK_{u,v}z} - e^{-\frac{\sigma^2}{2}} \right] \qquad \ldots\ldots\ldots\ldots..1$$

where $K_{u,v} = \begin{pmatrix} K_{ju} \\ K_{jv} \end{pmatrix} = \begin{pmatrix} K_v \cos\theta_u \\ K_v \sin\theta_u \end{pmatrix}$

where $K_v = \frac{f_{max}}{2^{v/2}}, \sigma = 2\pi,\ \theta_u = u\left(\frac{\pi}{8}\right)$ $and\ Z = image\ position$
The equation (1) is again simplified into

$$f_{u,v}(z) = \frac{D}{\sigma^2} e^{\frac{-D.E}{2\sigma^2}} \left[e^{F} \quad e^{-\frac{\sigma^2}{2}} \right]$$

where $D = \left(\|K_{u,v}\|\right)^2$, $E = (\|Z\|)^2$ and $F = iK_{u,v}Z$. The parameters D & E are calculated using l^2 norms. l^2-norm is defined as the square root of sum of squares of individual components. The l^2-norm is a vector norm defined for a complex vector. The l^2-norm is the vector norm that is commonly used in vector algebra and vector operations (such as the dot product), where it is commonly denoted by $|x|$. However, if desired, a more explicit (but more cumbersome) notation $|x|$ can be used to emphasize the distinction between the vector norm $|x|$ and complex modulus $|z|$. But the fact is that the l^2-norm is just one of the possible type of norms. The l^2 -norm of the vector $x = (x_1, x_2, x_3)$ is given by $|X| = \sqrt{x_1^2 + x_2^2 + x_3^2}$ and l^2-norm is represented as $\sqrt{\sum[Abs(A^2)]}$, where A=$max_{i \le j \le m} \sum_{i=1}^{m} |Z_{ij}|$. In the equation (1), '*u*' refers to the orientation and '*v*' refers to frequency, f_{max} is a constant. The equation (1) can be simplified further and one can get real and imaginary parts as shown in equation (2) and (3).

$$R_e(f) = -\frac{A}{\sigma^2} e^{f - \sigma^2/2} \qquad \text{.............2}$$

$$I_{mag}(f) = \frac{A}{\sigma^2} e^{f + icd} \qquad \text{.............3}$$

2.4. Daugman's Method

The real and imaginary parts of the Gabor wavelets are applied to the Daugman's Method proposed by Daugman's for demodulation. When the output of Gabor Wavelets is demodulated, each pixel in the resultant image is encoded to two bits [6]. This method is essential to split the Gabor Wavelets Pattern to GGPP and LGPP [6] and it is done by using the equation (4) and (5).

$$P_{u,v}^{Re}(z) = \begin{cases} 0\ if\ Re(G_{u,v}(z)) > 0 \\ 1\ \ if\ Re\left(G_{u,v}(z)\right) \le 0 \end{cases} \qquad \text{.............4}$$

$$P_{u,v}^{Im}(z) = \begin{cases} 0\ if\ Im(G_{u,v}(z)) > 0 \\ 1\ \ if\ Im\left(G_{u,v}(z)\right) \le 0 \end{cases} \qquad \text{.............5}$$

where $Re(G_{u,v}(z))$ and $Im(G_{u,v}(z))$ are real and imaginary parts of Gabor coefficient Daugman's encoding method can be reformulated as equations 6 & 7.

$$P_{u,v}^{Re}(z) = \begin{cases} 0\ if\ \theta_{u,v}\ (z) \epsilon\ I, IV \\ 1\ \ if\ \theta_{u,v}(z)\ \epsilon\ II, III \end{cases} \qquad \text{.............6}$$

$$P_{u,v}^{Im}(z) = \begin{cases} 0\ if\ \theta_{u,v}\ (z) \epsilon\ I, IV \\ 1\ \ if\ \theta_{u,v}\ (z) \epsilon\ II, III \end{cases} \qquad \text{.............7}$$

where $\theta_{u,v}(z)$ is the Gabor phase angle for the pixel at the position.

2.5. Formation of GGPP

GGPP scheme computes one binary string for each pixel by concatenating the real and imaginary bit codes of different orientations for a given frequency. Formally, the GGPP value, $GGPP_v(Z_o)$, for the frequency '*v*' at the position Z_o in a given image is formulated as the combination of Daugman's Values. By using this encoding method, a decimal numbers for each pixel corresponding to the real and imaginary GGPPs is obtained. GGPP scheme computes one binary string for each pixel by concatenating the real and imaginary bit codes of different orientations for a given frequency using equation (8) and (9).

$$GGPP_v^{Re}(z_0) = \left[P_{0,v}^{Re}(z_0), P_{1,v}^{Re}(z_0) \ldots \ldots \ldots P_{k,v}^{Re}(z_0)\right] \qquad \text{.............8}$$

$$GGPP_v^{Im}(z_0) = \left[P_{0,v}^{Im}(z_0), P_{1,v}^{Im}(z_0) \ldots \ldots \ldots P_{k,v}^{Im}(z_0)\right] \qquad \text{.............9}$$

The above equations give both real and imaginary GGPP. In this approach there are eight orientations representing 0-255 different orientation modes.

2.6. Formation of LGPP

LGPP is yet another encoding of local variations for each pixel. LGPP actually encodes the sign difference of the central pixel from its neighbors. LGPP reveals the spots and flat area in the given images. Formally, for each orientation '*u*' and frequency '*v*', the real LGPP value at the position Z_o is computed using local XOR pattern (LXP) operator [6, 7]. The local variation for each pixel obtained is LGPP. LGPP actually encodes the sign difference of the central pixel from its neighbors. LGPP reveals the spots and flat area in the given images using equation (10).

$$LGPP_{u,v}(Z_0) = P_{u,v}(Z_0) XOR P_{u,v}(Z_1), P_{u,v}(Z_0) XOR P_{u,v}(Z_2), P_{u,v}(Z_0) XOR P_{u,v}(Z_3), P_{u,v}(Z_0) XOR P_{u,v}(Z_4), P_{u,v}(Z_0) XOR P_{u,v}(Z_5), P_{u,v}(Z_0) XOR P_{u,v}(Z_6), P_{u,v}(Z_0) XOR P_{u,v}(Z_7) \quad \ldots\ldots\ldots\ldots..10$$

where Z_i, i = 1,2,...8 are the eight neighbors around Z_0, and *XOR* denotes the bit exclusive or operator.

3. ADAPTIVE BINNING TECHNIQUES

Histograms are used in image retrieval systems to represent the distributions of colors in images. The histograms adapted to images represent their color distributions more efficiently than histograms with fixed binnings. Adaptive histograms produce good performance, in terms of accuracy, less number of bins and efficient computation when compared to that of the existing methods for retrieval, classification, and clustering tasks. There are two general methods of generating histograms: i) fixed binning and ii) adaptive binning. Adaptive binning is similar to color space clustering in that k-means clustering. In other words, its variant is used to induce the bins. However, the clustering algorithm is applied to the colors in an image instead of the colors in an entire color space. Therefore, adaptive binning produces different bins for different images. The adaptive binning algorithm is applicable to a wide range of data and it is not limited to two dimensional data [8]. Adaptive binning is the simplest case of the algorithm. It attempts to adaptively bin a single image based on the number of pixels in each region. The basic method is to bin pixels in two dimensions by a factor of two, until the fractional Poisson error of the count in each bin becomes less than or equal to a threshold value. When the error is below this value, those pixels are not binned any further [9, 10].

3.1. Adaptive Binning Algorithm

Step 1: Put each pixel in a 'bin', which is a collection of pixels.
Step 2: The net count in the bin is defined by $s_i = c_i - n_i b$
Step 3: Fractional error in the bin is calculated as $\frac{\sigma(s_i)}{s_i} = \frac{\sqrt{c_i + n_i b}}{c_i - n_i b}$
Step 4: Find aveage mean count s_i/n
Fractional error <= threshold value in processed, find average mean count
else bin not yet processed
Step 5: Set Identification number for each processed bin
Step 6: Merge the neighboring bins.
Step 7: Repeat from Step 2 until a single bin is got

4. SPATIAL HISTOGRAMS

Object representation and feature extraction are essential to object detection. Specially, objects are modeled by their spatial histograms over local patches and class specific features are extracted. Spatial histograms consist of marginal distributions of an image over local patches and they can preserve texture and shape information about an object simultaneously [11]. GGPP & LGPP are relatively new and simple texture models proved to be a very powerful feature in classification of images [12]. GGPP & LGPP are invariant against any monotonic transformation of the gray scale and the basic GGPP & LGPP operator uses neighbourhood intensities to calculate the region central pixel value [1]. The 3 x 3 neighbourhood pixels are signed by the value of center pixel using the eq (11)

$$S_{(g_0,g_i)} = \begin{cases} 1, if\ g_i \geq g_0 \\ 0, if\ g_i \geq g_0 \end{cases} \ where\ i \leq i \leq 8 \quad \ldots\ldots\ldots\ldots..11$$

The signs of the eight differences are encoded into an 8-bit number to obtain LGPP value from the center pixel and calculated using eq (12)

$$\sum_{i=1}^{8} S(g_0, g_i)\ 2^{i-1} \quad \ldots\ldots\ldots\ldots..12$$

For any sample image, histogram-based pattern representation is computed as follows, first, variance normalization on the gray image to compensate the effect of different lighting conditions. And then basic global or local binary pattern operator is used to transform the image into an GGPP or LGPP image. Finally, histogram of an image is computed as its representation. It is easy to prove that histogram, a global representation of image pattern, is invariant to translation and rotation. However, histogram technique is not adequate, since it does not encode spatial distribution of objects. For irrelevant and relevant images, their histograms can be very similar or even identical, making histogram insufficient.

After using the spatial histograms and adaptive binning, a new pattern called HGPP is developed. It not only reduces data size but also involves less complexity. As a result, most of the unwanted data are removed and the performance increased. Using this HGPP Patterns, the test images for the specific database is checked and verified.

5. RESULTS AND ANALYSIS

This system uses a normalized image as input. Gabor wavelets, which are directly related to Gabor filter is a linear filter used for edge detection. A set of Gabor filers with different frequencies and orientations are helpful for extracting useful features from an image. In this system, frequency value is set to five and orientation to eight. Gabor filters has a real and an imaginary component representing orthogonal directions. So, in total, 80 (40 real and 40 imaginary) different sets of Gabor filters are obtained from a single image. These filters are further processed to demodulate the image by using Daugman's method. In this process, all the 80 images are demodulated to obtain quantified Gabor feature. After quantifying the Gabor features using Daugman's method, global Gabor phase patterns are generated to form a byte to represent 256 different orientation modes and a total of 10 (5 real and 5 imaginary) images are obtained in GGPP. To encode the local variations in a pixel, local Gabor phase pattern is applied to all 80 Gabor features using local XOR pattern. For five frequency and eight orientations, the phase patterns obtained will be 90 "images" (five real GGPP, five imaginary GGPP, 40 real LGPPs and 40 imaginary LGPPs), with the same size as the original image. To reduce the size of phase patterns, binning is done by using adaptive binning technique. Each phase pattern is taken and binned in such a manner that the count in each bin becomes less than or equal to the threshold value. To reserve the spatial information in the phase patterns, the GPP and LGP images are spatially divided into the non over-lapping rectangular regions, from which the spatial histograms are extracted. Then, all of these histograms are concatenated into a single extended histogram feature called HGPP. Formally, the HGPP feature is formulated as shown in eq (13)

$$HGPP = (H^{Re}_{GGPP}, H^{Im}_{GGPP}, H^{Re}_{LGPP}, H^{Im}_{LGPP}) \qquad \text{………….13}$$

where $H^{Re}_{GGPP}, H^{Im}_{GGPP}$ are the sub regions of real and imaginary part of GGPP and $H^{Re}_{LGPP}, H^{Im}_{LGPP}$ are the sub regions of real and imaginary part of LGPP. Final HGPP representation is a local model robust to local distortions caused by different imaging factors such as accessory, expression variations.

5.1. Input Image Database

The database is developed into 3 different sizes, such as 64x64, 88x88 and 128x128. Based on the face image factors, images are categorized into 10 parts as shown in Table 1. In each size of image, the images are categorized into 10 parts as shown in Table 1. The images resized in three different sizes are viz. 64x64, 88x88 and 128x128.

Image Factor Type	Description
Aging	Aging subjects
Dup I	Subsets of Aging
Dup II	
Fa	Frontal
Fb	Expression
Fc	Illumination

TABLE 1: Classification of Image Database

5.2. Output - Gabor Wavelets

The images to be trained are given as input to the Gabor functions, where the Gabor wavelets are obtained. The sample Gabor wavelets obtained for images are shown in the figure 2 & 3. In the proposed system, the frequency and orientation of an image are increased by keeping the frequency (v) to five and orientation (u) to eight. For real and imaginary part of a single trained image, the database will have eighty images.

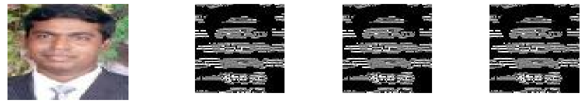

FIGURE 2: Images after applying Gabor Function (Frequency)

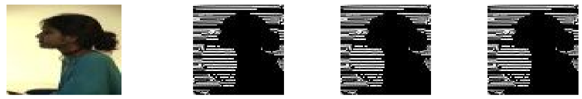

FIGURE 3: Images after applying Gabor Function (Orientation)

5.3. HGPP Patterns

Figure 5 and 6 shows the patterns obtained after applying the HGPP and Adaptive binning respectively for the images shown in Figure 4. From the figure, reduction in the size of the data for an image can be observed.

FIGURE 4: Image used

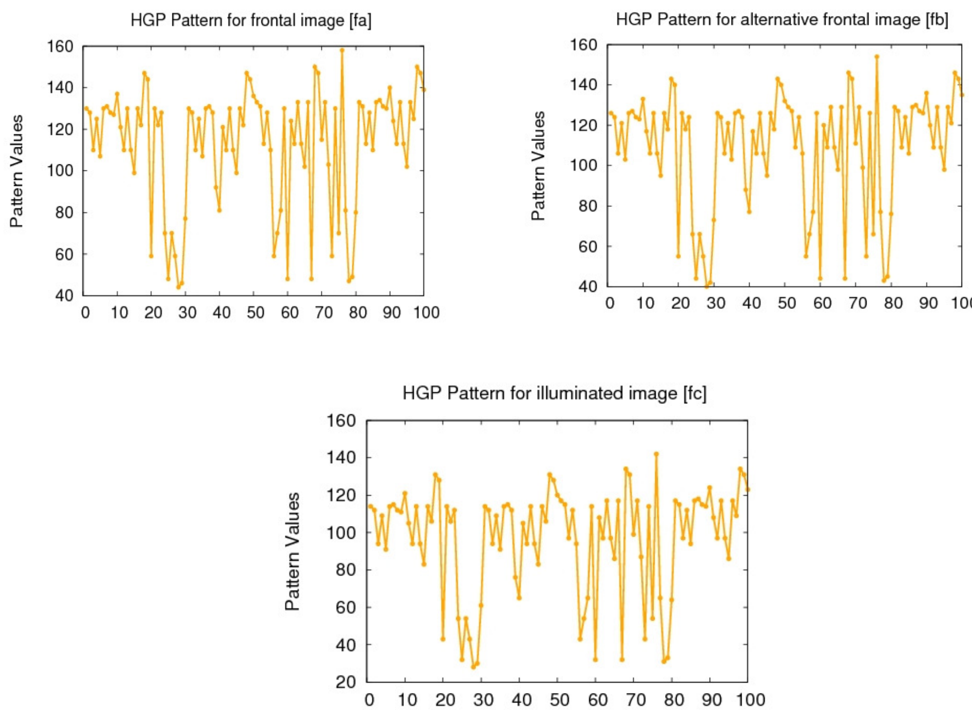

FIGURE 5: HGP Patterns for three image types

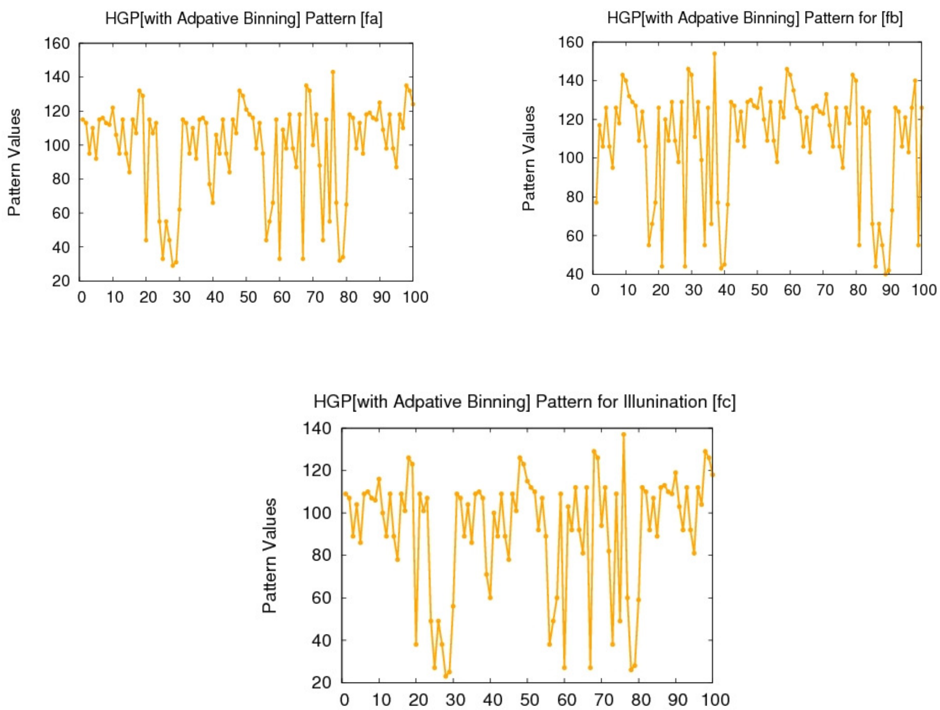

FIGURE 6: HGP Patterns using Adaptive binning for three image types

The recognition rates for different sizes of images are tabulated in the Table 2 and the results plotted are shown as Figure 7. To further validate the effectiveness of HGPP, these results are compared with those available in methods such as Feature Extraction, Eigen Face and HGPP (i.e. without using Adaptive Binning Method). The results clearly indicate that the proposed HGPP method outperforms all the other methods, especially on the Dup I, and Dup II probe set. Experimental results of this comparison evidently prove that the proposed HGPP method achieves best results on our database. Since the face images in our database probe sets contain several source of variations such as expression, lighting, and aging, these comparisons indicate that HGPP is impressively robust to these extrinsic imaging conditions. Gabor features can exhibit the spatial frequency (scale), spatial locality, and orientation selectivity properties corresponding to Gabor wavelets. Adaptive Binning is a kind of quantification of Gabor feature contributing to the robustness of HGPP.

Probe Size	Fa	Fb	Fc	Aging	Dup I	Dup II
64x64, $f_{max} = 3.14$	99.12	98.32	97.48	92.00	89.1	84.11
88x88, $f_{max}=1.11$	99.78	98.74	97.89	93.00	88.66	83.62
128x128, $f_{max}=1.57$	98.34	99.58	99.16	91.00	89.51	85.71

TABLE 2: Recognition rates in percentage for different sizes of image data base.

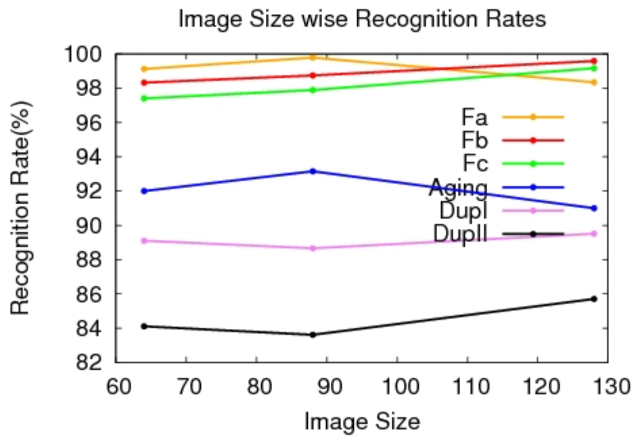

FIGURE 7: Recognition rate for different sizes of images and for probe sets (HGPP)

It can be seen From the Table 2 that when the image is 64x64 better recognition rates are obtained for frontal images [Fa] then for alternative frontal images [Fb]. For illuminated images [Fc] the recognition rates decrease to some extent when compared with the Fa and Fb. For aging [Dup1], one gets less recognition rate value because of the resolution change in the image. f_{max} plays a vital role for getting better recognition rate, when size of image increases and f_{max} value decreases, recognition rate is improved. But in case of 128x128 sized images, f_{max} value has to be increased to get the better efficiency. Hence, fixing the appropriate value of f_{max} plays an important role to get improved performance rate.

Figure 7 shows the graph version of Table 2. The graph is drawn with image size as x-axis and recognition rate as y-axis. It can be seen from the graph that when the image size increases, there is a linear increase in recognition rate, when the image size increases, the clarity of image increases. As a result, the efficiency increases and the time taken to process the image also increases.

Methods	Image Database Probe Set					
	Fa	Fb	Fc	Aging	Dup I	Dup II
Feature Extraction [FE] Method	93.15	93.25	94.56	83.75	85.23	81.25
Eigenfaces [EF] Method	95.78	95.89	95.12	85.12	87.21	82.56
HGPP [HGP] Method	98.00	96.13	96.89	91.75	88.85	83.65
HGPP(with Adaptive Binning) [ADP] Method	99.00	98.32	97.48	92.15	89.10	84.11

TABLE 3: Recognition Rate Comparison for various methods

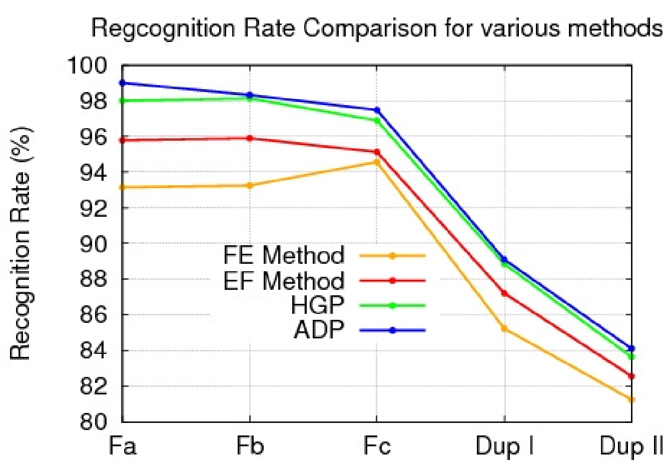

FIGURE 8: Recognition Rate Comparison for various methods

Table 3 presents the efficiency rate comparison for various methods such as Feature Extraction, Eigen Face, HGPP, and HGPP with Adaptive Binning methods. The comparison is done with face image factors such as frontal image [Fa], alternative frontal image [Fb], illuminated image [Fc], and aging images [Dup I and Dup II]. Transforming the input data into set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the feature set will extract the relevant information from the input data. Using this reduced representation desired task is performed instead of the full size input. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately because a number of variables are involved in simplifying the data. Analysis with a large number of variables generally requires a large amount of memory and computation power. It is because of more memory and computation power, the recognition rate efficiency goes down.

In Eigenfaces, a set of eigenfaces are generated by performing a mathematical process called principal component analysis on a large set of images depicting different human faces. Informally, eigenfaces can be considered a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. And also, it does not take many eigenfaces combined together to achieve a fair approximation of most faces. Each eigenface represents only some features of the face which may or may not be present in the original image. If the feature is present in the original image, then the contribution of that eigenface in the sum of eigenfaces will be greater. Otherwise it achieves a very low approximation of faces. It is because of data loss, the recognition rate efficiency goes down and because of less computation cost and memory, the rate is more than that of the Feature Extraction method.

As regards HGPP, the normalized image is given as input to the Gabor wavelets, from where a lot of processed images are obtained, and these images are given as input to Daugman’s and LGP, and GGP patterns are generated and processed with spatial histogram. In this process, HGP patterns are obtained involving a huge amount of data. It is because of this, the time taken for processing and the computational cost are increased. Whereas in Adaptive Binning concept, the pattern obtained after HGPP are binned. Since most of the data are binned here, the computational time decreases and recognition rate efficiency increases. It can be seen from Figure 8 showing the graph version that there is a linear increase in recognition rate efficiency for different face image factors for Adaptive binning method [ADP].

Table 4 tabulates the results of different imaging factors such as frontal image [Fa], alternative frontal image [Fb], illuminated image [Fc], and aging [Dup1]. The methods compared are Feature extraction method, Eigen Faces method, HGPP and Adaptive binning method. For the last two methods, the comparison is also done by calculating mean values and without calculating mean values. Without mean the computational time increases, but with mean, the checking time reduces and efficiency increases.

	FE Method	EF Method	HGPP Method		ADP Method	
			Mean	Without Mean	Mean	Without Mean
Frontal [Fa]	93.15	95.78	99.12	98.00	95.65	98.45
Alternative Frontal [Fb]	93.25	95.89	98.25	96.13	98.36	97.32
Illumination [Fc]	94.56	95.12	97.58	96.89	98.46	97.48
Aging			91.75	92.00	92.15	93.50
Dup I	85.23	87.21	88.85	89.50	89.1	90.00
Dup II	81.25	82.56	83.65	84.00	84.11	85.15

TABLE 4: Experimental Results

It can be seen From Table 4 for frontal images [Fa] that the recognition rate is good in all the methods listed. But, for the images with background light effects the rate goes down to some extent because of illumination. For an illuminated image, our proposed system gives an increased efficiency than other methods do. Calculation of mean value for generated HGP patterns gives an significant increase in efficiency because of reduced data size in comparison. This can noticed in the figure 9. For aging image factor, when mean is calculated then the efficiency percentage is 95.89% compared with that of 93.85% in HGPP method, when binning concept is used, efficiency percentages remain 97.45 and 95.10 respectively.

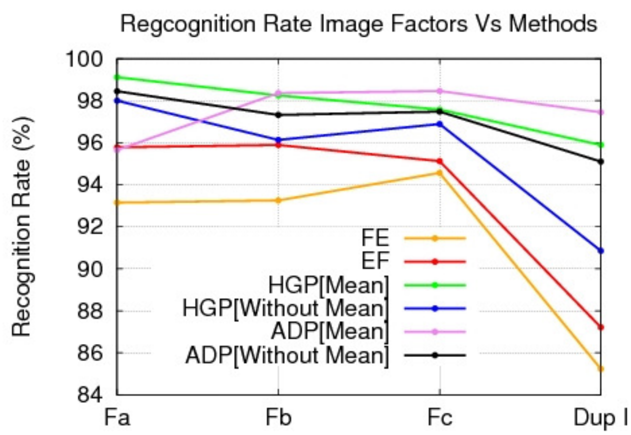

FIGURE 9: Recognition Rate Comparison

6. CONCLUSION

The proposed new system using HGPP and adaptive binning technique gives good recognition rate for different image factors. In this system, the computational complexity arising due to the huge volume of database is reduced and it gives opportunity to extend the database size. A possible future work in this regard could be fixing the appropriate f_{max} value. Further, efficiency could be increased by using modified algorithms for classification and boosting techniques.

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