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Face Recognition using Hough Transform based Feature Extraction

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Abstract

The sensitivity to illumination variations is a challenging problem in Face Recognition (FR). In this paper, a novel feature extraction method based on Hough Transform peaks is proposed to address this problem. Individual stages of the FR system are examined and an attempt is made to improve each stage. Block-wise Hough Transform Peaks are used for efficient feature extraction and a Binary Particle Swarm Optimization (BPSO) based feature selection algorithm is used to search the feature space for the optimal feature subset. Experimental results, obtained by applying the proposed algorithm on benchmark face databases, namely, Extended Yale B, CMU PIE, CAS-PEAL and Color FERET databases, show that the proposed system outperforms other FR systems by accounting for the illumination variations that are commonly observed in face images.

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Keywords: Face Recognition; Feature Extraction; Hough Transform; Binary Particle Swarm Optimization

1. Introduction

Face Recognition (FR) system is a process of identification/verification by an artificial system through the comparison of facial features of various images of a facial database. FR systems are extensively used in the fields of image analysis, access control for security facilities, computer systems, automobiles and in authentication processes [1]. Under the conditions of varying illumination, error rates below 1% at a false accept rate of 1 in 1000 were reported in the Face Recognition Vendor Test (FRVT) and the Multiple Biometric Evaluation (MBE) 2010 [2,3,4]. Conventional feature extraction processes use Fourier Transform, Discrete Wavelet Transform and Principal Component Analysis. The effectiveness of feature extraction is best determined by its ability to discriminate facial features [5].

The variation in illumination and pose should be minimized for optimal face recognition, and hence pre-processing of training and testing images must be done. In this paper, a new feature extraction technique built on Hough Transform (HT), and based on the extraction of significant hough peaks is proposed. Hough Transform was invented by Hough, in 1959, for machine analysis of bubble chamber photography [6]. This method was patented under the name Method and Means for Recognizing Complex Patterns, as U.S. Patent 3,069,654 in 1962. Hough transform is widely used as a feature extractor in various pattern recognition systems and one such method is explained in detail [7].

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The pre-processed images enhance the recognition process and the results improve significantly when applied to databases. The different pre-processing techniques used, feature extractor and feature selector concepts are explained in Section 3. The proposed methodology is explained in Section 4. In Section 5, experiments and results are discussed and conclusions have been drawn in Section 6.

2. Problem Definition and Proposed Contributions

In this paper, a new feature extraction technique using Hough Transform (HT) is proposed to perform face recognition. The number of HT peaks obtained by the application of HT to an entire image varies for each image and this leads to redundancy during feature extraction. To overcome this, the image is divided into a number of blocks, causing a part of the image to be present in each block. The block size depends on the number of blocks the image is segmented into. The aspect ratio of the original image and the block image is maintained constant. After applying HT, the number of peaks obtained again vary for different blocks of the image. Hence, a set of prominent peaks are extracted to maintain the gallery size constant. The number of peaks extracted from each block is dependent on the block image size and the number of blocks the image is segmented into. *The main contribution of this paper is block-wise division of image and extracting significant feature peak points from each block.*

3. Fundamental concepts

The basics of pre-processing techniques used in the paper are explained in Section 3.1. Edge Detection technique, which is necessary for working of Hough Transform, is explained in Section 3.2. The Hough Transform is used as the feature extractor which picks out the important features and BPSO is used for feature selection, which selects the best features. The Hough Transform and BPSO concepts are dealt in Section 3.3 and 3.4 respectively.

3.1. Image Enhancement Techniques

Image enhancement techniques are applied to images in order to highlight the required features for efficient face recognition. The contrast of images is enhanced using certain methods mentioned in this paper. Background removal techniques are also used to improve face recognition by removing the redundant components from the image.

Histogram equalization (HE) is an efficient method of image pre-processing in which the contrast of the image is uniformly equalized using the histogram of the image. This process is done by remapping the gray levels of the image based on the probability distribution of the input gray levels [8]. The overall range of the image's histogram increases, and hence improving the overall contrast of the image as seen in Fig. 1a [9]. *Logarithmic transform (LT)* is used to map a narrow range of low intensity values to a wider range of high intensity values and also maps the longer range of high intensity values to a narrow range of high intensity values [10]. The mapping function of this operator takes the fashion of a logarithmic curve, i.e. the natural logarithm of each pixel intensity is calculated and multiplied by a constant as depicted in Eq. 1.

$$F = c * \log(1 + p) \tag{1}$$

where p describes the normalized pixel intensity in the image and c is a constant. Depending upon the value of this constant, the contrast of the image can be varied and adjusted accordingly. The Log Transform of an image with a factor of 0.2 and 0.4 is shown in Fig. 1b. *Gamma intensity correction (GIC)* is a non-linear process of adjusting the lightness or darkness of an image. The gamma value, when less than 1, darkens the image and lightens the image for values greater than 1 [11]. The gamma corrected image for a factor of 4 is shown in Fig. 1c.

Unsharp masking (UM) is an image sharpening technique which uses a blurred positive image to create the mask of the original image. The image is blurred using low pass filter in frequency domain and subtracted from the original image to give a masked image, which is added with the original image to give final unsharped image. This process is controlled by two parameters, namely, radius of filter and threshold. The radius controls the amount of blurring and the threshold restricts the sharpening activity to the pixels whose difference from their neighbours exceeds a specified threshold value. *Background Removal (BR)* is the process of extracting unwanted background in image which hinders the face recognition process. Hence, these have to be removed in a way such that the facial part of image is not lost in the process. This is done by using skin color segmentation to detect the skin regions of the face and extracting only the detected part of image by using scale normalization technique[12]. This process is illustrated in Fig. 2. *Mirror Fusion (MF)* is used in order to compensate the variation of pose in the system, to provide better results. This was done by flipping the original image and fussing it with the original image. For instance, if the image was right profile, then after mirroring, it consists of equal shares of both profiles[13]. This improves the recognition rate by about 5-10%.

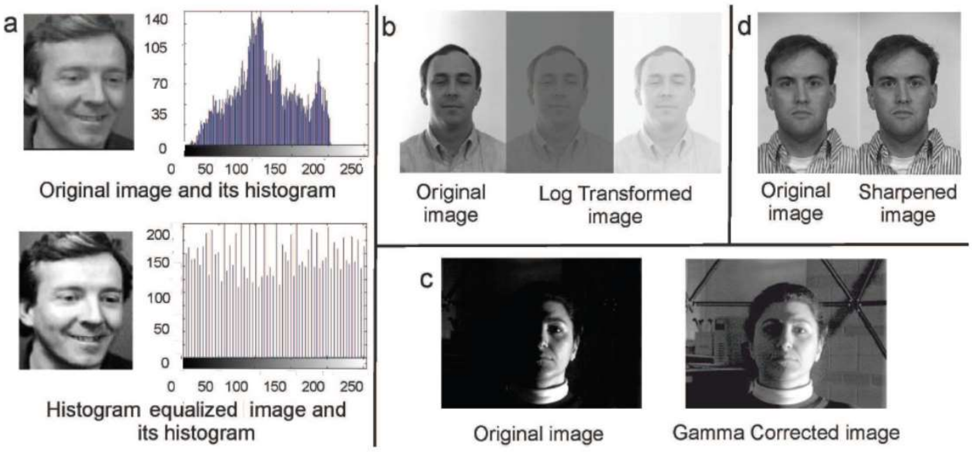

Fig. 1 Illustrates different image enhancement techniques. (a) shows Histogram Equilization, (b) Logarithmic Transform, (c) Gamma Correction, (d) Sharpening of image using unsharp masking.

3.2. Edge Detection (ED)

Edge Detection is a mathematical operation which identifies the changes in the brightness of the image. The points where the variation in the brightness of the image is abrupt are organised into a set of curved segments called edges. These edges are used to examine the changes in properties of the environment. The edges obtained after the edge detection process are subjected to dilation for better differentiation of the edges from the surrounding portions of the image. Sobel operator is used for edge detection in this paper, which is illustrated in Fig 3.

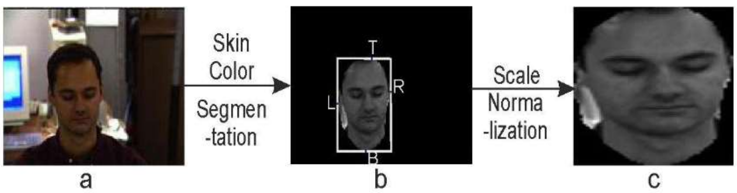

Fig. 2 Depicts the background removal process. (a) is the original image, (b) Skin detected image, (c) Scale normalization of (b).

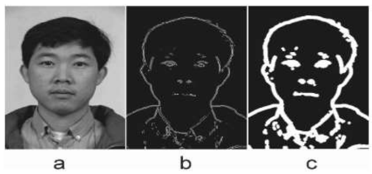

Fig. 3 Illustrates the edge detection process. (a) is the original image, (b) shows the edge dection, (c) shows the dilation of edge image.

3.3. Hough Transform (HT)

Hough transform is used in pinpointing the arbitrary shapes like lines, circles, ellipses in images from the structure of object contours encountered in the image[14]. This process is undergone through a voting scheme, which is carried out to obtain the best peak values in the parameter space. In this paper, the process is concentrated on Standard Hough Transform (SHT), which is used to determine straight lines. A straight line can be described by Eq. 2.

$$y = mx + c \tag{2}$$

where m-slope of the line and c-is the y-intercept of the line. For a robust computation process, Duda and Hart proposed to use a different parameter space, defined by rho (ρ) and theta (θ) for better detection of lines using Hough transform [15]. The equation of the line can be expressed by Eq. 3.

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{\rho}{\sin\theta}\right) \tag{3}$$

where ρ is the perpendicular distance of the line from the origin and θ is the angle subtended by the line with respect to one of its axis (usually x-axis) as shown in Fig. 4a. Thus, Eq. (3) can be rearranged as shown in Eq. 4 [10].

$$\rho = x\cos\theta + y\sin\theta \tag{4}$$

The basic idea of Hough Transform is understood by considering a point in the spatial domain given by (x,y), obtained from the edge detection process, where every edge detected point is intersected by infinite number of lines which subtend different angles with respect to x-axis and vary in their algebraic distance from the origin as illustrated in Fig. 4b. Thus, each point votes for a series of values of (ρ, θ) for all the lines passing through it. A line in an edge detected image consists of many points voting for that particular line segment [16]. The line which gets a larger share of votes is the line of interest and it depicts the region of facial features of the image.

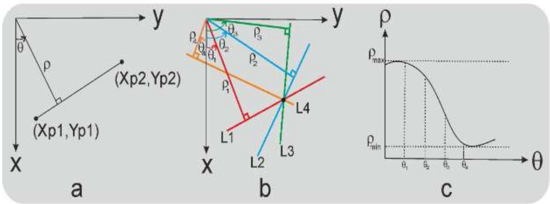

Fig. 4 Basic Principle of HT. (a) shows representation on equation of straight line, (b) illustrates intersection of many lines to a point, (c)Transformation of point in image space to polar space.

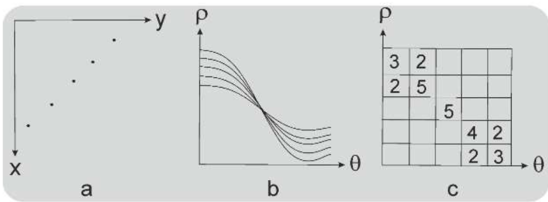

Fig. 5 Working of HT as feature extractor. (a) shows a set of points in image space, (b) illustrates convergence of points in image space to sinusoidal waves in polar space, (c) represents the accumulator space.

During the implementation, the spatial co-ordinate system (x,y) is converted to polar co-ordinate system given by (ρ,θ). Similar to spatial domain, the polar domain is also made discrete in terms of (ρ,θ). For a particular value of x and y, i.e. a specific point in spatial domain, when the values of theta is varied, the rho values change in a sinusoidal fashion Fig. 4c. Thus, for every point in edge detected image, it gives a sinusoidal wave in the accumulator space and there exists a particular region which begins to accumulate more number of votes, which signifies the line with many feature points as depicted in Fig. 5. To detect these feature vectors, the maxima of the accumulator space is considered to compute the feature parameter extracted.

3.4. Feature selection using Binary PSO (BPSO)

Particle swarm optimization (PSO) was originated in 1995 by Kennedy and Eberhart by observing the social behavior of birds or fish [17]. PSO is a robust computation method of optimizing a problem through an iterative process of computing results and improving it to obtain the best result. PSO consists of a finite number of particles in the search-space.These particles move around looking for the best solution which optimizes the problem.

Let $X_i(t)$ be the present position of the i^{th} particle and $V_i(t)$ be the present velocity of the particle at an instant of time t. The position and velocity is updated and is shown by Eq. 5 and Eq. 6 respectively.

$$V_i(t+1) = \omega \times V_i(t) + c_1 \times rand_1 \times (pbest_i - X_i(t)) + c_2 \times rand_2 \times (gbest - X_i(t)) \tag{5}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{6}$$

where $pbest_i$ is the best position attained by that particle at the instant t, $gbest$ is the best position attained by any of the particles, ω is the inertial weight, c_1 is the cognitive factor, c_2 is the social factor, $rand_1$ and $rand_2$ are two random numbers with uniform distribution U(0,1).

A binary PSO algorithm has been developed in [18]. The position of the particle is coded as a binary string. The coordinate may take either 0 or 1 as values. In BPSO, the *sigmoid* function is used which is given by Eq. 7.

$$\sigma(V_i(t+1)) = \frac{1}{1+e^{-V_i(t+1)}} \tag{7}$$

where $V_i(t+1)$ is the updated velocity. Then, the position of the particle is described by using Eq. 8.

$$X_i(t+1) = \begin{cases} 1 & if\ rand_3 < \sigma(V_i(t+1)) \\ 0 & elsewhere \end{cases} \tag{8}$$

where $rand_3$ is a random number in (0,1).

Fitness function: In BPSO, the evolution of the particle is governed by the fitness value associated with that particle. This methodology is applied as its main function is to increase the class separation and hence optimize the face recognition process. The class mean is calculated from Eq. 9.

$$M_i = \frac{1}{N_i}\sum_{j=1}^{N_i} W_j^{(i)}\ ,\ i = 1,2,3.......L \tag{9}$$

where M_i represents the class mean, $W_j^{(i)}$ represents the sample images from class w_i. The grand mean M_0 is given by Eq. 10.

$$M_0 = \frac{1}{N}\sum_{i=1}^{L} N_i M_i \tag{10}$$

where N is the total number of images for all the classes. The Fitness value F is given by Eq. 11.

$$F = \sqrt{\sum_{i=1}^{L}(M_i - M_0)(M_i - M_0)^T} \tag{11}$$

where T denotes the transpose of the matrix.

Euclidean classifier: The similarity measurement between the test vectors and the reference vectors in the face gallery is done using the Euclidean classifier. The feature vectors obtained from the training images are the reference vectors. The selected feature vectors obtained from the test images are the test vectors. Euclidean distance between two vectors a_k and b_k is given by

$$Euclidean\ dist. = \sqrt{\sum_{k=1}^{N}(a_k - b_k)^2} \tag{12}$$

4. Proposed Methodology: Block-wise Hough Transform Peaks (BHTP)

Prior to the application of Hough Transform on an image, the image is segmented into smaller blocks [19]. For each block, Hough Transform is applied and the specific number of feature points are extracted. The block size reduces when the number of blocks is large, due to which the image content present in the block is also reduced, leading to better extraction of features. Thus, for each block, the number of features present is less and extraction of these features leads to precise choosing of the prominent peaks. This can be observed in Fig. 6. The block size is decided by the number of blocks the image is segmented into. For N number of blocks, the image consists of $\sqrt{N}$ number of blocks along rows and $\sqrt{N}$ number of blocks along columns. The block image dimension is given by Eq. 13.

$$Block\ width\ (Bw) = \frac{Image\ width}{\sqrt{N}} \quad and \quad Block\ height\ (Bh) = \frac{Image\ height}{\sqrt{N}} \tag{13}$$

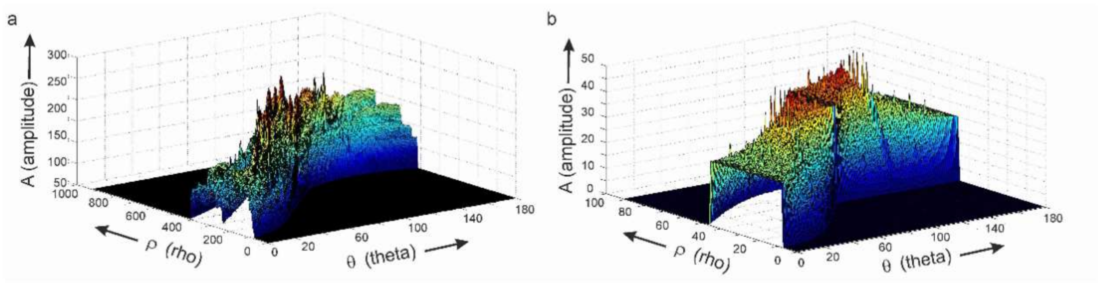

Fig. 6 Illustrates the advantage of taking blocks for Hough Transform (HT). (a) shows HT for entire image and (b) HT for a single block image.

Desired number of peaks from each block have to be considered for the feature gallery. This number is critical, as large number of peaks might exist for a block and taking lesser number of peaks leads to loss of some prominent features. If more peaks are considered, then it influences the extraction of unwanted feature points which leads to a reduction in the recognition rate. A threshold is specified to extract hough peaks, it is chosen based upon the Eq. 14.

$$Peaks = \frac{(SAR) \times (BAR)}{(Nb/100)} \times \alpha \tag{14}$$

where *SAR*- Std. aspect ratio of images taken as 4:3, *BAR*- Block aspect ratio given by $Bw : Bh$, *Bw* is the block image width, *Bh* is the block image height, *Nb* is the number of blocks the image is segmented into and α is the constant whose optimum value is found out to be 16 through experimentation. This can be represented by Eq. 15. The block size and number of peaks considered for different databases, is illustrated in Table 1 for block division of 400 blocks.

$$Peaks = \frac{4 \times (Bw) \times 16 \times 100}{3 \times (Bh) \times (Nb)} \tag{15}$$

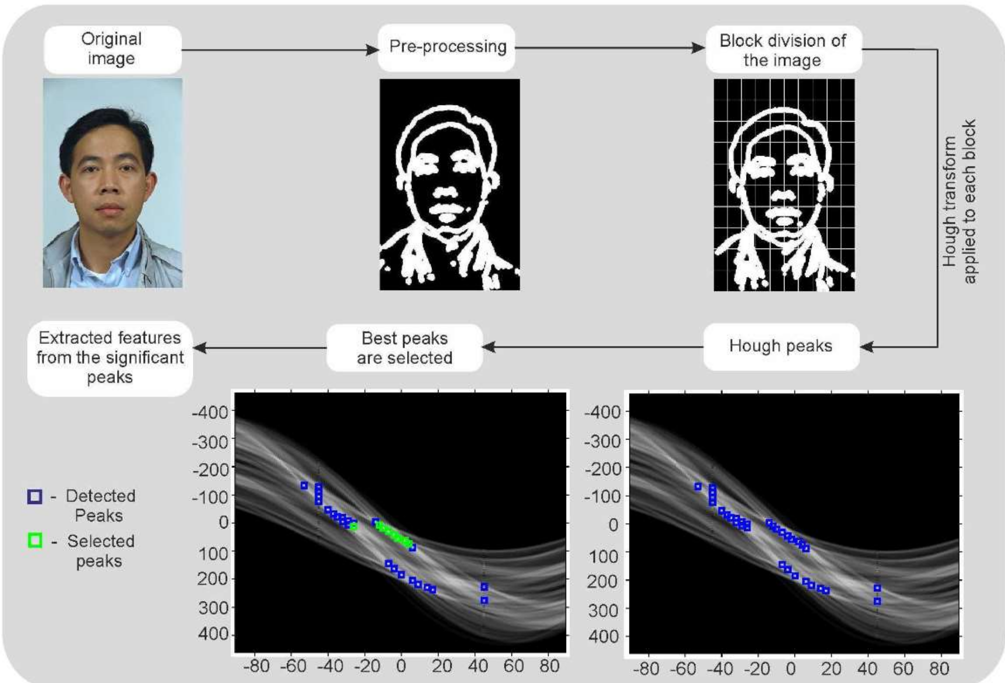

Fig. 7 Process flow of operations in the proposed system. The pre-processed image is obtained and partitioned into a set of blocks, HT is applied to each block to extract a particular number of prominent peaks.

Proposed method: The proposed method is explained as per the steps given below & the same is illustrated in Fig. 7:
Step 1: The original image is enhanced through contrast improvement techniques to emphasize on the facial part of the image. In case of CMU PIE (Original), background removal is used to remove the unwanted regions of the image
Step 2: This enhanced image is subjected to Sobel edge detection and dilated to mark out the regions of high intensity
Step 3: The binary image obtained is partitioned into many blocks to separate the region of interest
Step 4: Hough Transform is applied to each block of the image, converting the image space to accumulator space
Step 5: The local maxima are considered as the prominent peaks and their positions are determined
Step 6: From the prominent peaks determined, the hough value of feature points is extracted

5. Experimental results and discussions

Experiments were conducted in order to estimate the performance of the system against variations in pose, illumination, expression, and with unwanted background present. Five different databases were customized in order to conduct these experiments as depicted in Table 1. All experiments were implemented on MATLAB R2013a [20] and tests were run on a PC powered by Intel Core i7 Processor with clock frequency of 2.4GHz and 8GB of RAM. Different pre-processing steps considered for each databases are depicted in Table 2. All experimental results are obtained by considering the average of 10 iterations.

5.1. Experiment 1: Illumination variation

5.1.1. CAS-PEAL Database

CAS-PEAL is a large-scale Chinese face database for training and evaluation with different sources of variations, especially, Pose, Expression, Accessories, and Lighting (PEAL) [21]. A subset of the whole CAS-PEAL face database, named as CAS-PEAL-R1, is provided as an open source for experimentation. It contains 30,863 images of 1,040 subjects and is categorized into frontal and non-frontal subsets. The frontal subset is further divided based on lighting variations. The images are captured with 15 different illumination conditions. In a spherical coordinate system, whose origin is the center of the circle that coincides with the semi-circular shelf, these positions are located at the crossover of five azimuths (−90°, −45°, 0°, +45°, and +90°) and three elevations (−45°, +0°, and +45°) [22]. 3 lighting sources are provided, Ambient (E), Florescent (F) and Incandescent (L) lighting. There are 233 subjects which have images with atleast 9 lighting changes. This database is formed by considering 3 azimuths (0°, ±45°, ±90°) for all 3 elevations with Florescent lighting and 0° azimuth for 0° elevation with Incandescent lighting. Thus, 10 images for 40 subjects are taken. The optimum result was obtained for 400 blocks by considering 7 peaks. The feature vector size is 2,800. The variation in rates for different number of blocks and train to test ratios are tabulated in Table 3 and Table 4 respectively.

5.1.2. Extended Yale B Database

Extended Yale B [23] contains 16,128 images of 28 human subjects under 9 poses and 64 illumination conditions. A total of 19 images from subset 5 has been used for each of the 28 subjects. The size of each image is 640×480. This database requires only two pre-processing steps, namely, Log Transform and Edge Detection. The variation of parameters with respect to segmented blocks in depicted in Table 3. The best rates are obtained by considering 400 blocks of the image and by taking 7 peaks from each block. The total feature vector size is 2,800. The variation in parameters using this condition is observed for various train to test ratios and gave very slight error or 100% recognition as tabulated in Table 4.

5.2. Experiment 2: Pose, Background and illumination variation

CMU PIE is a complex database which has wide variation in pose, background and illumination [24]. The database consists of 41,368 color facial images of 68 individuals. The images in the custom CMU PIE database have severely cluttered background. Pose varies from full left profile to full frontal and onto full right profile. These images exhibit 13 poses, 43 illumination conditions, and 4 expressions. This database is customised into two parts:

- *Original:* The database is created by considering 30 different subjects and choosing 13 images randomly. Background removal is essential to separate out the facial parts of the image. The images are resized to 168×128 before background removal. The optimum results were obtained when the image is partitioned into 400 blocks where the number of peaks considered from each block was 7 peaks. The total feature vector size is 2,800.

- *Illum:* The customization of the database was done by choosing 10 images each for 20 subjects. The images have varying expression and illumination conditions, but no variation in the pose. The changes in parameters with respect to number of blocks was found to be premium when the image was divided into 400 blocks with 7 peaks extracted from each block as shown in Table 3. The total feature vector size is 2,800.

Table 1 Description of the Database: Variations in images are symbolized by s-scale, p-pose, i-illumination, b-background & e-expression variance.

Database	Image variations	No. of classes	Images per class	Gallery size	Original image size	Resized value	Block image size (for 400 blocks)	No. of peaks
CAS-PEAL	i	40	10	400	480 × 360	480 × 360	24 × 18	7
Extended Yale B	i	28	19	532	640 × 480	640 × 480	32 × 24	7
CMU PIE (Original)	b, p, i	30	13	390	640 × 486	168 × 128	8 × 6	7
CMU PIE (Illum)	i, e	20	10	200	640 × 486	640 × 486	32 × 24	7
Color FERET	s, p, i	35	20	700	384 × 256	384 × 256	19 × 13	8

Table 2 Pre-processing techniques used on different databases.

Database	Background Removal	Histogram Equalization	Logarithmic Transform	Gamma Correction	Unsharp Masking	Edge Detection	Mirror Fusion
CAS-PEAL			✔		✔	✔	
Extended Yale B			✔			✔	
CMU PIE (Original)	✔	✔	✔	✔	✔	✔	✔
CMU PIE (Illum)			✔			✔	
Color Feret		✔	✔	✔	✔	✔	✔

Table 3 Experimental results for different number of blocks.

Database	No. of blocks	No. of peaks	Avg. rate (%)	Selected features	Training time (s)	Testing time (ms)
CAS-PEAL	100	28	87.17	1809	150.21	91.56
	225	13	91.58	1987	162.68	102.52
	400	**7**	**93.75**	**1783**	**190.06**	**101.05**
	625	5	93.67	1983	200.88	102.19
	900	4	92.83	2266	216.55	153.71
Extended Yale B	100	28	99.33	1878	141.37	63.60
	225	13	99.46	1858	195.96	87.45
	400	**7**	**99.95**	**1793**	**219.94**	**98.74**
	625	5	99.86	1986	243.50	108.57
	900	4	99.91	2280	291.85	129.33
CMU PIE (Original)	100	28	30.67	1795	106.45	63.14
	225	13	30.08	1864	114.32	68.68
	400	**7**	**32.41**	**1787**	**125.10**	**77.48**
	625	5	31.25	1994	153.09	91.70
	900	4	30.33	2292	175.34	101.90
CMU PIE (Illum)	100	28	98.33	1769	82.68	83.32
	225	13	98.66	1862	98.67	90.88
	400	**7**	**99.50**	**1758**	**100.42**	**102.15**
	625	5	98.17	1977	115.59	106.72
	900	4	99.17	2278	124.59	143.17
Color FERET	100	32	75.42	2031	206.61	69.14
	225	14	77.00	2005	214.53	67.84
	400	**8**	**80.81**	**2042**	**247.60**	**85.09**
	625	5	77.90	1976	268.24	86.88
	900	4	77.09	2292	325.94	105.47

Table 4 Experimental results for different Train:Test ratios.

Database	Tr. : Te. ratio	Avg. rate (%)	Selected features	Training time (s)	Testing time (ms)
CAS-PEAL	2:8	89.06	1785	191.16	83.97
	4:6	93.75	1783	190.06	101.05
	5:5	94.25	1774	192.08	103.62
	6:4	95.40	1771	195.84	110.50
	8:2	96.25	1784	202.00	115.98
Extended Yale B	3:16	99.95	1793	219.94	98.74
	6:13	99.92	1802	232.25	97.23
	9:10	100	1780	253.62	98.20
	11:8	100	1776	254.62	98.73
	13:6	100	1783	273.87	98.60
CMU PIE (Original)	3:10	26.84	1789	124.97	74.00
	5:8	32.41	1787	125.10	77.48
	6:7	35.54	1787	131.60	77.17
	8:5	37.86	1784	134.47	74.48
	10:3	40.89	1779	140.04	75.95
CMU PIE (Illum)	2:8	96.88	1770	113.39	137.32
	4:6	99.50	1758	100.42	102.15
	5:5	99.60	1766	131.28	142.24
	6:4	100	1758	136.85	156.42
	8:2	100	1772	110.00	117.70
Color FERET	6:14	73.65	2041	268.92	87.16
	8:12	80.81	2042	247.60	85.09
	10:10	82.22	2026	256.56	81.25
	12:8	84.78	2037	333.65	97.78
	14:6	88.85	2035	317.83	118.94

The different pre-processing steps involved in the recognition process for this database is shown in Table 2. The fluctuation in parameters for different train to test ratios was computed for the above conditions and gave satisfactory results as shown in Table 4.

5.3. Experiment 3: Pose and lighting variation

Color FERET database[25] contains 11,338 color facial images of 994 individuals. FERET consists of following subsets: frontal images (fa,fb), quarter left (ql), quarter right (qr), profile left (pl), profile right (pr), half left (hl), half right (hr) and rotated images (ra,rb,rc). The customization of the database was done by choosing 2 images from each subset and 4 images from rotated set which makes a total of 20 images. This was done randomly for 35 classes. The pre-processing techniques used on this database are shown in Table 2. In this experiment, immense variations in parameters were observed due to the variation of the number of blocks considered for Hough Transform. These values are tabulated in Table 3 and it was found to give the best result when the image was divided into 400 blocks. The variation of recognition rate based on the number of peaks considered was also observed and was found to be 8 peaks from each block. The total feature vector size is 3,200. Thus, the change in parameters for different train to test ratios were calculated using 400 blocks, with 8 peaks, to obtain results which are shown in Table 4.

5.4. Experiment 4: Experimental observations and comparison with other FR Systems

Different techniques used are HE - Histogram Equalization, LT - Log Transform, GIC - Gamma Intensity Correction, UM - Unsharp Masking, MF - Mirror Fusion, ED - Edge Detection and BHTP - Block-wise Hough Transform Peaks. Variations using these techniques are tabulated in Table 5. It can be concluded that Log Transform plays an important role while dealing with illumination variations and the system performs the best for pose variance when all the mentioned techniques are used.The systems performance is compared against other FR Systems which are based on different illumination invariant and pose invariant processes, and is summarized in Table 6.

Table 5 Experimental observations of recognition rates (%)

Technique used	CAS-PEAL	Extended Yale B	CMU PIE (Original)	CMU PIE (Illum)	Color Feret
ED+BHTP	92.67	87.33	27.16	94.28	63.72
HE+ED+BHTP	78.83	97.90	30.92	96.00	63.72
LT+ED+BHTP	92.58	**99.95**	26.75	**99.50**	72.38
HE+LT+ED+BHTP	83.41	97.99	27.58	86.83	79.05
HE+GIC+ED+BHTP	83.75	93.88	28.08	87.83	78.57
LT+GIC+ED+BHTP	80.83	95.22	23.91	88.50	72.48
HE+UM+ED+BHTP	74.66	97.63	29.25	95.67	64.76
LT+UM+ED+BHTP	**93.75**	99.83	25.83	96.50	64.76
HE+LT+GIC+ED+BHTP	82.00	93.70	25.67	87.50	78.33
HE+LT+UM+ED+BHTP	83.33	96.30	29.25	88.83	79.05
HE+LT+GIC+UM+ED+BHTP	82.16	93.26	27.50	85.83	70.00
HE+LT+GIC+UM+MF+ED+BHTP	71.75	92.86	**32.41**	95.16	**80.81**

Table 6 Comparison Table.

Database	Tr. : Te.	Method used	Avg. RR (%)
Extended Yale B	4:15	DDFFE+ThBPSO[26]	99.73
	3:16	SIET+ Threshold based DWT+BPSO[27]	97.00
		Proposed method	**99.95**
CMU PIE (Illum)	2:8	HF+IF+RSM+DWT+DCT+BPSO[28]	88.21
		LT+LHT+DCT+DOFS+SEC[13]	92.75
		Proposed method	**96.88**
Color FERET	8:12	DFT+DCT+BPSO[29]	80.23
		Proposed method	**80.81**

6. Conclusions

A unique method for feature extraction using Block-wise Hough Transform Peaks, has been proposed in this paper. It can be inferred from Table 3 that high recognition rates and reduced feature subsets have been obtained using only discriminant features which contribute towards recognition. The results obtained on applying the proposed method to face databases that have variations in illumination (Extended Yale B, CMU PIE, CAS-PEAL), illustrate the robustness of the system. The proposed method has performed well under severe illumination variations with an average recognition rate of 99.95% for subset 5 of Extended Yale B considering 400 blocks. Reduction in the number of features used for classification, decreases testing times, improving the speed of the FR system. On a PC with Intel i7 2.4 GHz CPU and 8 GB RAM, the proposed method costs an average testing time per image of 98.74 ms with a training to testing ratio of 3:16 for Extended Yale B database. This may still be a limitation of the proposed technique for real time applications. Hence, a future research issue could be to develop fast computation methods.

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