ROBUST FACE RECOGNITION WITH AGE GROUP ESTIMATION

[1]A.VIJI [2]Dr.V.VAIDEHI

[1]Department of Electronics Engineering, Anna University, MIT campus, Chennai, India.

[2]Vellore Institute of Technology, Chennai, India.

[1]mailvijis@gmail.com, [2]vaidehi.vijayakumar@vit.ac.in

Abstract**—***An efficient Illumination and Pose Invariant (IPI) methodology to recognize human faces under uncontrolled lighting and the age of the recognized faces is proposed in this paper. Face recognition is based on robust pre-processing followed by fusion of Extended Curvature Gabor wavelets (ECG) and Local Binary Patterns (LBP) to extract the features of curvature information and the texture information of face image respectively. As both feature sets are higher in dimension, PCA is used to reduce the dimensionality prior to Z-Score normalization. Nearest Neighbour classifier is used to recognize the face. Support Vector Machine based Regression algorithm is used to estimate the age of a face in an image. The proposed IPI method found to give better recognition accuracy than the existing methods available in the literature. The results of the proposed system are evaluated using Extended Yale-B database and our self collected MIT India database of different age groups*.

Index Terms**—** *facial feature extraction, fusion, face recognition, age group estimation, Extended Curvature Gabor wavelet.*

1. Introduction

In today's digital age, face recognition plays a paramount role in computer vision applications. Automated Face recognition has recently received significant attention during the past years. This is due to its trending use in a wide range of commercial and law enforcement applications. It is used in many surveillance applications and human computer interaction systems. Though many face recognition techniques have been proposed in the past few decades, it is still a challenging task. There may be a reduction in the error rates for Face images captured in a controlled environment (test database). The results are different from that of the test database of the face recognition system in real-time environment condition. The performance appreciably deteriorates due to the variations in facial pose, facial expression and illumination effect in an uncontrolled environment. The accuracy can also be affected by the image quality (e.g. Resolution, blur, and compression), facial aging and occlusion.

Human face information is usable in many interesting applications, one of the most fascinating being automated age classification. Broadly speaking, automatic age classification aims to assign a label to a face regarding the exact age or the age group it belongs. The problem has inspired researchers leading to a diverse set of solutions, but a significant remark among the proposals is that their feasibility has been mainly evaluated in controlled settings. It is required to improve classification in more general and realistic scenarios. Recent developments in face recognition imply that it is a field with huge research potential. Although numerous methods for face recognition exist in literature, there is a demand for scale, pose, and illumination invariant algorithm.

The paper is organized as follows: Section 2 briefly discusses about the related works. Section 3 provides the proposed methodology. In Section 4 Experimental results are discussed in detail. Conclusion and future work are discussed in Section 5.

2. Literature Survey

In the existing literature, many face recognition approaches and age group estimation are discussed to tackle illumination problems of the face image. The Spherical Harmonic method (Wang et al 2004) requires many images to build the linear space model which is a difficult task while handling large database [1]. The enhancement techniques free from any training are Quotient Image method, Self-Quotient Image, Gamma correction, DoG filtering, Contrast equalization and Histogram equalization (Wang et al 2004).

The face is recognized based on the illumination invariant features such as 2D Gabor-like filters, the discrete cosine transform and Local Binary Pattern (Ojala et al 1996) [2]. Elastic Bunch Graph

Matching (EBGM) is a feature-based face recognition algorithm which has been used to determine the facial attributes from an image. It extracts the texture using Gabor wavelets around a set of biometric landmark points on a face, and generates a level graph. Gabor features have been extensively used for facial image analysis due to their powerful representation capabilities. Their work focuses on selecting and combining multiple Gabor classifiers that are trained with different scales and local regions. The system exploits curvature Gabor features in addition to conventional Gabor features.

Feng et al. (2000) proposed a sub-band approach using PCA on wavelet Transform. Traditionally, to represent the human face, PCA is performed on the whole face image [3]. Wavelet transform is used to decompose an image into different frequency sub-bands, and a midrange frequency sub-band is used for PCA representation.

Georghiades et al. (2001) proposed appearance-based method for recognizing human faces under variation in lighting and viewpoint. Their method performs well without error except in the extreme lighting directions [4].

Several illumination normalization methods are investigated and proposed by Shan et al. (2003) [5]. The main contribution includes a normalization method using the Gamma Intensity Correction (GIC) to the overall image intensity. The Histogram Equalization (HE) and a region-based strategy combining GIC is proposed to further eliminate the side-lighting effect.

Zhang et al. (2004) proposed an efficient face recognition scheme based on 2D wavelet sub-band coefficients and a modular, personalized classification method based on kernel associative memory models [6].

Ahonen et al. (2004) proposed a novel approach for face recognition [7]. Both the texture and shape information is considered to represent the face images. The features are extracted by dividing the face area into small regions in the Local Binary Pattern (LBP) histogram method and the resultant value are concatenated into a single, spatially enhanced feature histogram efficiently representing the face image.

Zhang et al. (2005) proposed a scheme based on Gabor Wavelet Network (GWN) and Kernel Associative Memory (KAM), into a unified structure called Gabor Wavelet Associative Memory (GWAM) [8].

Meedeniya & Ratnaweera (2007) proposed a method based on the variation of Principal Component Analysis (PCA) technique [9].

Tan & Triggs (2007) have used Gabor wavelets and Local Binary Pattern (LBP) to get better performance for face recognition [10]. LBP captures small appearance details. Gabor features encode facial shape over a broader range of scales.

Wu et al. (2009) proposed a work based on wavelet transform for face recognition with large variations of pose, expression and lighting [11]. Discriminant features are extracted by the wavelet transform-based method from two source images. One source image is a holistic gray value image and another is an illumination invariant geometric image. Face sample is reconstructed by the adaptive fused discriminant feature extraction method.

Tan & Triggs (2010) proposed a solution for uncontrolled lighting conditions [12]. The problem is tackled by illumination normalization, distance transform based matching, local texture-based face representations, kernel-based feature extraction and multiple feature fusion. Two complementary sources-Gabor wavelets and LBP are used by showing that the combination is considerably more accurate than single feature set.

Hwang et al. (2011) proposed a framework for face recognition based on Extended Curvature Gabor (ECG) Classifier Bunch [13]. This is done by extending Gabor wavelet kernels into the ECG wavelet kernels by the addition of a spatial curvature term to the kernel and by adjusting the width of the Gaussian at the kernel which results in extraction of numerous feature candidates from a low resolution image. Significant features are selected by applying Linear Discriminant Analysis (LDA).

Jun et al. (2011) proposed an illumination-robust face recognition technique [14]. Both the combination of the statistical global illumination transformation and the non-statistical local face representation methods are used for illumination-robust face recognition technique.

Susan & Chandna (2013) focused on the Gabor Wavelet representation of the image [15]. It is mainly used for fuzzy logic for determining the 'soft' class label of the colour test images.

Chai et al. (2014) used Gabor ordinal measures (GOM), which integrates the distinctiveness of Gabor features and intra-person variations in face images [16]. Many kinds of measures are derived from real, phase, magnitude, and imaginary components of Gabor images. Finally, greedy block selection method and two-stage cascade learning method are used to train a strong classifier for face recognition.

Ueki & Kobayashi (2015) focused on deep learning algorithm for face recognition [17]. In their work, Convolutional Neural Networks (CNNs) are compared with conventional methods such as Bag-of-Features (BoF) using local descriptors. The multi-layer structure of CNNs is introduced for the classification pipeline of the BoF framework.

Ueki et al. (2006) presents a framework of age-group classification using facial images under various lighting conditions [18]. The appearance-based approach projects the images from the original image space into a face-subspace for feature extraction using 2DPCA and LDA.

Geng et al. (2006) proposed the AGES (AGing pattErn Subspace) method for automatic age estimation [19].

Guo et al. (2008) uses a Support Vector Machine Regressor (SVR) for learning the relationship between codes face representations and age [20]. First a global SVR is used for a rough age estimation which is followed by a local SVR within a small interval around the initial age estimation to obtain refined age estimation.

Wang & Tang (2009) proposed an age categorization method based on Error-Correcting Output Codes (ECOC) to the fused Gabor and LBP features of a face image to categorize a person into one of four possible age groups (child, teen, adult and senior adult) [21]. Age categorization (multi-class learning problem) is solved using the combination of ECOC with SVM.

Chen et al. (2010) proposed an image-based age-group classification method to estimate three age groups, namely child, adult and the elder [22]. After face detection 52 feature points are located using Lucas-Kanade image alignment method. These feature points and the located facial areas are used to build an Active Appearance Model (AAM). The texture features are applied to Support Vector Machine (SVM) to estimate the age group.

Kim et al. (2015) proposed an automatic age estimation method via Extended Curvature Gabor (ECG) features and a learning-based technique [23]. Instead of conventional Gabor Filters, ECG filters are used to extract curvature information from a face image, which is useful for the estimation of age. The feature selection method is used to reduce the computational complexity. Their approach proves the effectiveness of ECG features. The regression algorithm is used to estimate the age of the test face image and the performance is compared with other recent works in terms of age estimation.

Jana et al. (2015) proposed a methodology to analyze the wrinkle area of face images to estimate the age of a human. Wrinkle features are extracted from the face image [24]. The face image is clustered using fuzzy c-means clustering algorithm. The age is calculated using the clustering membership value and the average age of each cluster.

Reddy & Karumuri (2016) proposed an algorithm for automatic age classification [25]. Central Pixel Flooding Matrix (CPFM) based on shape pattern was used to classify child and adult person. The CPFM forms a textured image over the facial image by considering neighbouring pixels which have the same intensity as a central pixel. The shape patterns on CPFM of facial images are calculated and these features are used for age classification.

For an efficient real time face recognition system, it is of importance that the algorithm must work under all lighting conditions. Most of these algorithms fail to work under varying lighting conditions. In summary, it is found that there is a need for an efficient face recognition technique that has better performance in terms of recognition accuracy under pose, expression and illumination variation.

The current age estimation performance in terms of accuracy is not good in the uncontrolled environmental condition. Hence this paper proposes an efficient algorithm to address the above inadequacy in the existing literature. In summary, it is found that there is a need for an efficient age group estimation technique that has better performance in terms of accuracy under pose, expression and illumination variation. This paper proposes an efficient Illumination and Pose Invariant (IPI) methodology to recognize human faces and to estimate the age group of the human faces considering the above mentioned problem.

3. Proposed Methodology

In the proposed work, a simple and efficient pre-processing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition is used. The architecture for the robust face recognition system with age estimation is shown in Figure 1. The pre-processed image is convolved with a bank of ECG filters at different scales and orientations. LBP features are also used for illumination invariant feature extraction. The ECG and LBP of the pre-processed input image are reduced in dimension using PCA. The resulting features are normalized using z-score method. The fusion of LBP and ECG is employed and the nearest neighbour classifier uses the distance measure to recognize faces.

Many pattern recognition systems use one type of feature only. However, in complex tasks such as face recognition more than one class of features is required to capture the relevant information. Therefore, incorporating rich local appearance cues from two most successful local face representations and the complementary sources such as ECG wavelets and LBPs, gives a considerably better performance than either alone.

The two feature sets are complementary in the sense that LBP captures small appearance details while ECG wavelets encode facial shape over a broader range of scales. Thus face recognition accuracy is improved by combining two complementary feature sets.

The score fusion phase is performed where the weighted summation rule is employed to fuse the normalized scores of the face image and the nearest neighbour classifier is utilized to recognize the unknown user.

Experiments are also performed using the resultant fused features to estimate the age of the face using the SVM classifier. Age estimation for an individual and a group of face images is done using different database and discussed in detail.

3.1 Pre-Processing Technique

The performance of face recognition systems is affected by the variations due to pose and illumination. Pre-processing the image is the only solution to this problem.

The pre-processing in the proposed method combines the features of gamma correction, Difference of Gaussian (DoG) filtering and contrast equalization techniques named by Tan and Trigg's (2010) [12]. This pre-processing chain incorporates a series of stages designed to counter the effects of illumination variations, local shadowing, and bright lighting while preserving the essential elements of visual appearance. The pre-processing stages are shown in Figure 2.

The processed outputs of the pre-processing stages are shown in Figures 3(a) and 3(b) for different database. The effects of illumination variations, local shadowing are eliminated and the essential elements of visual appearance are highlighted.

3.2 Feature Extraction Techniques

The second stage is the feature extraction stage. In the feature extraction stage, the important information in the image is extracted and the additional information is removed for classification. The pre-processed image is given as input to different feature extraction techniques for analyzing the performance. Extended Curvature Gabor, Local Binary Pattern and the combination of both are used for feature extraction.

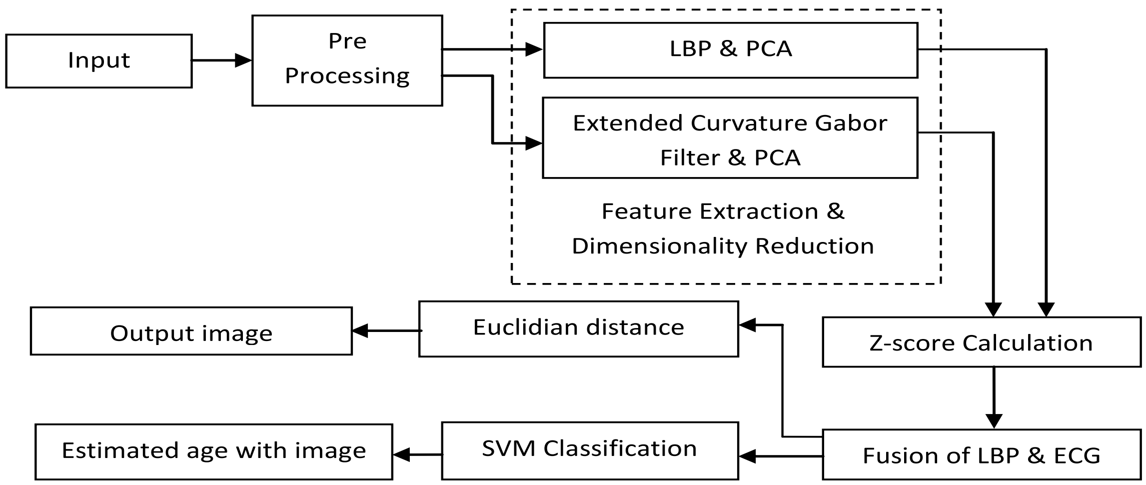


Fig. 1 An Efficient IPI method for face recognition and age estimation

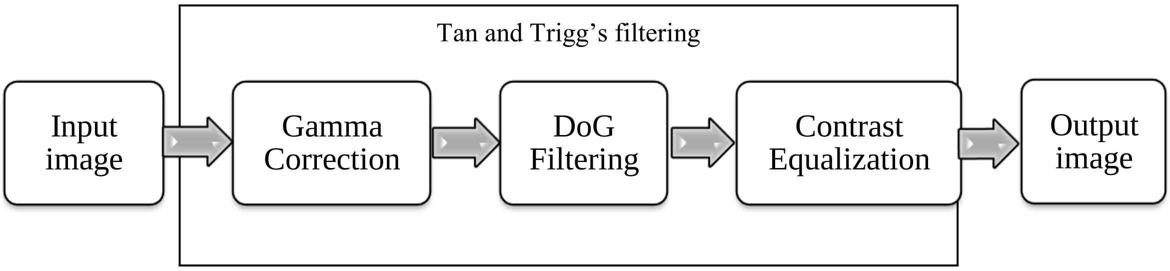
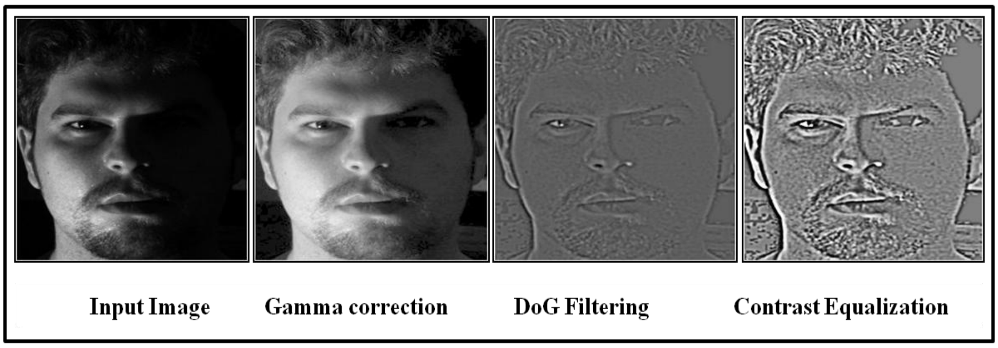


Fig. 2 Pre-processing chain of Tan and Trigg's filtering

(a) Example of pre-processed output stages of the illuminated image (MIT India database)



(b) Example of pre-processed output stages of the illuminated image (Extended Yale B database)

Fig. 3 Removal of effects of illumination variations by TT-filtering

3.2.1Feature Extraction using Extended Curvature Gabor

Feature extraction techniques are used to get the relevant information which is important among the whole information. The Extended Curvature Gabor is the extended version of Gabor wavelet Transform. Gabor expansion is one kind of sampled Short Time Fourier Transform (STFT) which gives good time-frequency trade-off. Gabor transform can be expressed as a summation of mutually orthogonal time-shift and frequency-shift Gaussian function.

The ECG kernels are obtained by adding a spatial curvature term to the kernel and adjusting the width of the Gaussian kernel, which leads to numerous features being extracted from a single image. Peters & Kruger (1997) have extended the concept of Gabor wavelets to banana wavelets by adding a curvature parameter for object representations [26]. The face image is composed of a mixture of curved shape components. The eyes, nose, and cheeks of a face image have curvature characteristics which are important for face analysis. The curvature Gabor kernels are more suitable for extracting the curved facial features than the original Gabor kernels. The ECG wavelets are defined as follows:

$$\psi(\vec{x}, v, \mu, c) = \frac{k_{v,\mu}^2}{\sigma^2} e^{\left(-\frac{k_{v,\mu}^2 \|\vec{x}\|^2}{2\sigma^2}\right)} \left[e^{(ik_{v,\mu}x')} - e^{\left(-\frac{\sigma^2}{2}\right)}\right] \quad (1)$$

$$x = \begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} xcos\varphi ysin\varphi + c(-xsin\varphi + ycos\varphi)^2 \\ -xsin\varphi + ycos\varphi \end{pmatrix} \quad (2)$$

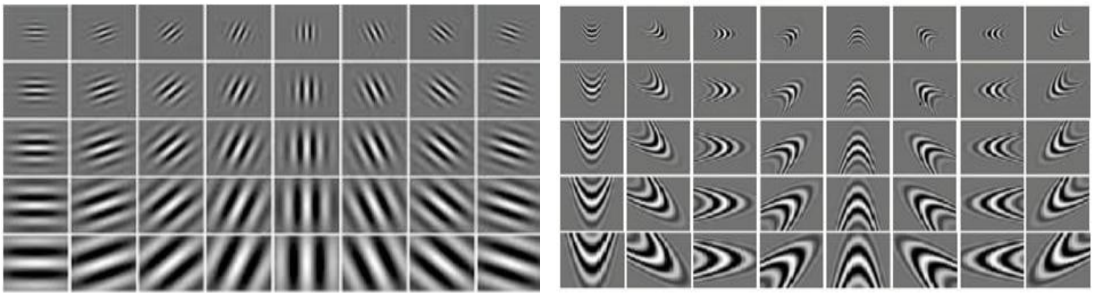
where the curvature ratio c ϵ {0, 0.05, 0.1, 0.15, 0.2}

$$k_v = 2^{-\left(\frac{v+2}{2}\right)}\pi \text{ and } \varphi_\mu = \mu\left(\frac{\pi}{8}\right) \quad (3)$$

where v represents different frequencies (scales) and μ represent orientations. For v = {0, 1, 2, 3, 4} and μ = {0,1,.....,15} it is possible to get a 5×16 discrete ECG wavelet kernel set. The value of σ = 2 π represents the radius of the Gaussian kernel size. If the curvature degree is not zero, the number of orientations used in ECG wavelets increases to 16. For c = 0, it is simply the conventional Gabor wavelet.

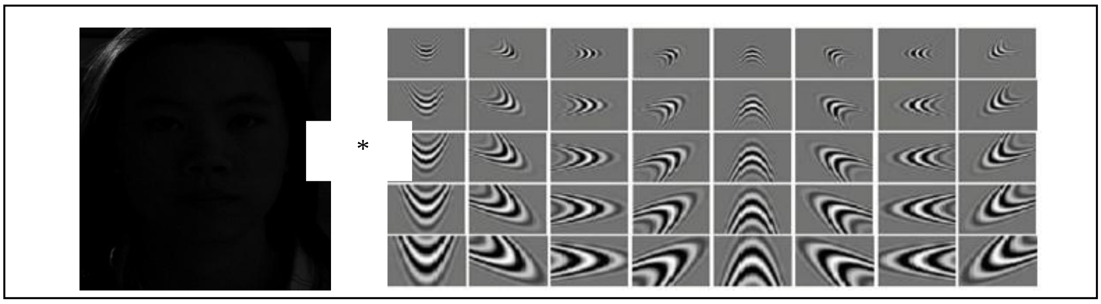
Gabor Wavelet kernels and ECG wavelet kernels for different orientation and scale are shown as an example in Figures 4(a) and 4(b). The convolution of an ECG wavelet with the face image is performed to obtain the ECG magnitude Images at different scales and orientations. ECG filter bank is a complex number and hence the convolution operation is done separately for real and imaginary part. ECG extracts curvature information such as wrinkles of face images more effectively, which is shown in Figure 5.

The input image is convolved with ECG kernels as shown in Figure 5(a). The resulting feature extracted for with and without pre-processing stage is shown in Figures 5(b) and 5(c). From Figures 5(b) and 5(c) it is clear that the information extracted after the pre-processing stage is more visible compared to without pre-processing stage.

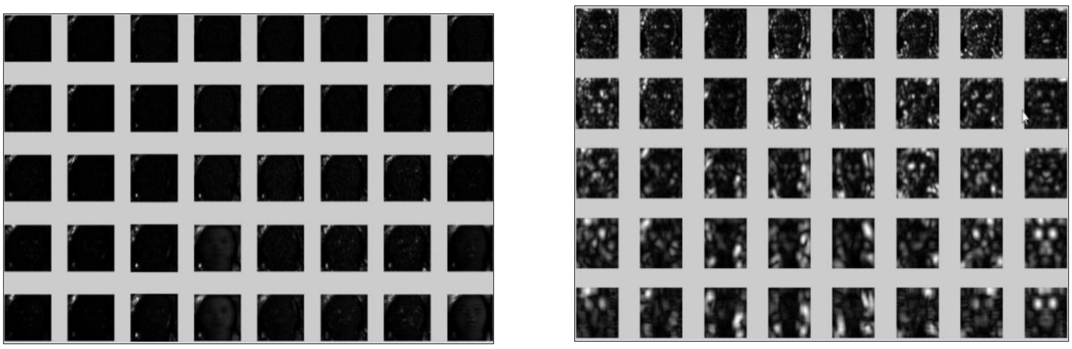


(a) Gabor kernels (b) ECG kernels

Fig. 4 Conventional Gabor Vs ECG kernels



(a) Convolution of input image with ECG kernels



(b) ECG feature without pre-processing (c) ECG features after pre-processing

Fig.5 ECG feature extraction

3.2.2 Feature Extraction using Local Binary Pattern

Ojala et al. (1996) introduced Local Binary Pattern (LBP) [2]. LBP is a computationally efficient non-parametric local image texture descriptor. LBP features are invariant to monotonic gray-level changes due to illumination variations and require no image pre-processing before use. LBP can be used as a lighting normalization stage for face recognition. The image is split into blocks.

The size of the block is 3 × 3 pixels of an image. The thresholds of the pixels in the block are fixed by its centre pixel value. If the centre pixel value is lesser than the neighbourhood pixel value, then that pixel is replaced by one else its value is replaced with zero. The resultant value is multiplied by powers of two and then summed to obtain a value for the centre pixel.

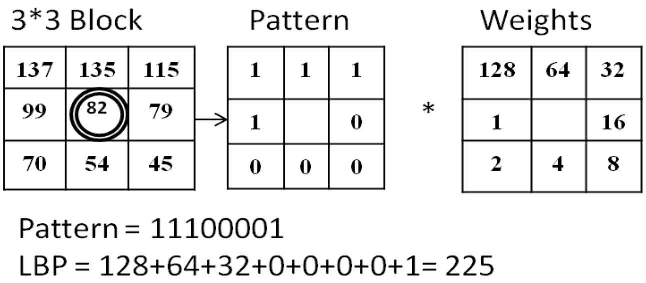
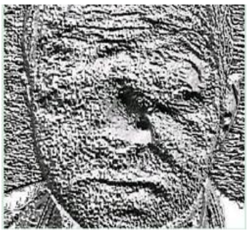


Fig. 6 Illustration of LBP Technique

(a)Input image



(b) LBP feature without pre-processing

(c) LBP feature with pre-processing

Fig. 7 The Resultant LBP Image

A total of 2^8 = 256 different labels can be obtained depending on the gray values of the centre pixels. Formally, the LBP operator takes the form

$$LBP(x, y) = \sum_{n=0}^{7} 2^n \, s(i_n - i_c) \quad (4)$$

where in this case, ‘n’ runs over the 8 neighbours of the central pixel ‘c’, i_c and i_n are the gray-level values at ‘c’ and ‘n’, and s(u) is ‘1’ if $u \geq 0$ and ‘0’ otherwise.

The LBP encoding process is illustrated with example and is shown in Figure 6. The central pixel value is replaced by the calculated LBP value at the same position of the original image. In this example, the centre pixel 82 is replaced with 225. The resultant value extracted from a gray scale image is then used to form histograms that are the feature vectors. The illuminated image used to extract the feature of LBP along with and without pre-processing technique is shown in Figure 7. The curvature information is clearer in Figure 7(c) than in Figure 7(b).

3.3 Normalization and Fusion of LBP and ECG Features

The ECG wavelet and the LBP features are extracted separately from the pre-processed image. The resulting features are given as input to PCA to reduce the dimensions. They are used to compute the corresponding distance scores. Each score is normalized using the “z-score” method by using the Equation (5). The steps involved in fusion are shown in Figure 8.

$$z = \frac{s(x,y) - \mu}{\sigma} \quad (5)$$

where s, μ, z and σ are feature vector, the mean vector, z-score and standard deviation vector respectively over the training set. Finally, the two scores z_{ECG} and z_{LBP} are fused at the decision level. The proposed work fuses the Gabor and LBP similarity scores using the simple sum rule:

$$z = z_{ECG} + z_{LBP} \quad (6)$$

The resulting similarity score is given as input to a simple distance measure for recognition and SVM classifier to find the age group for the final decision.

3.4 Classifier for Face Recognition and Age Group Estimation

The features of a face probe image are compared with the template stored in the face database to find the similarity measure. Nearest Neighbour (NN) classifier is the simplest method mostly used for face recognition to make the decision. SVM classifier is used to find the age group for the recognized face.

3.4.1 Nearest Neighbor Classifier for Face Recognition

Nearest Neighbour (NN) classifier is used to measure the similarity between the probe image and gallery image. There are two ways in general to measure similarity. One way is to find the distance between the image features. The other possibility is to measure the similarity of the image features. The distance between two feature set is given by the Euclidean distance as given in Equation (7).

$$d_j(x,y) = \sqrt{\sum_{i=1}^{L}(x_i - y_{ij})^2} \quad (7)$$

where, d_j (x, y) is the distance between test image features x_i and y_{ij} is the training feature set. Here L is the number of features in the feature set for j^{th} training image. The minimum distance value is the nearest match for the test image.

3.4.2 SVM Classifier for Estimation of Age Group

Support Vector Machines (SVM) is used as a binary classifier to classify the age group. The traditional way to perform multi-class classification with SVMs is to use one-versus-all classification. SVM is used to perform linear classification and can efficiently perform a non-linear classification using the kernel trick and implicit mapping of their inputs into high-dimensional feature spaces. SVM is required to train a model that will classify the different age group images for the given training set.

The goal of SVM for linearly separable binary sets is to find a hyper-plane that will classify all training vectors into two classes. For example, if there are two classes represented by red and blue dots, then a Linear SVM will easily classify by finding the line which separates the two classes. Though there are many lines which could separate this data, SVM chooses the maximum distance data points of either class. Figure 8 shows the linearly separable SVM classifier. The aim of the SVM classifier is to estimate a decision function by constructing the optimal separating hyper plane in the feature space as in Equation (8).

$$w.x + b = 0 \quad (8)$$

Now, all hyper planes in the region are parameterized by a vector (w), and a constant (b), expressed in the equation.

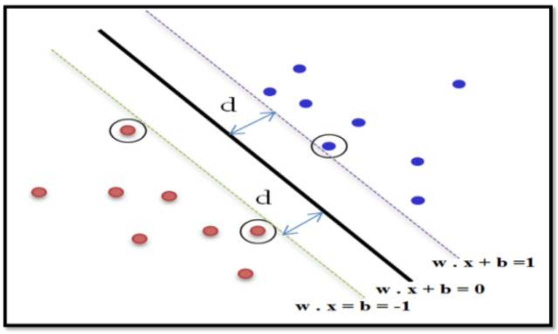


Fig.8 Representation of a Linear SVM

Linear classification

Given a set of training data pairs (x_i, y_i), $y_i \in \{+1, -1\}$, the output is given by

$$w.x_i + b \geq +1 \text{ when } y_i = +1$$
$$w.x_i + b \leq -1 \text{ when } y_i = -1$$
$$y_i(w.x_i - b) \geq 1 \quad (9)$$

where y_i is either 1 or −1, each indicating the class to which the point x_i belongs. Legranges multiplier α is introduced in the above Equation and the constrained Equation can be obtained by Equation (10). The aim of optimization is to minimize the function given by the following expression.

$$f(x) = (\sum_i \alpha_i y_i \langle x_i, x\rangle + b) \quad (10)$$

4. Results and Discussion

The face recognition of proposed IPI method is done by the convolution of the pre-processed image with a bank of ECG filters at different scales and orientations. LBP features are also extracted separately to remove the effect of illumination. The features extracted from the ECG and LBP are reduced in dimension using PCA. The resulting features are normalized using z-score method. The fusion of LBP and ECG is performed and the nearest neighbour classifier based distance measure is used to recognize faces. The results of the proposed work using Extended Yale-B database under different pose and lighting conditions are presented below.

Experiments are also performed using the resultant fused features to estimate the age of an individual and a group of face image using SVM classifier. The proposed IPI methodology is evaluated using the MIT real-time database having different subjects belonging to various age groups with the different pose and lighting conditions.

4.1 Results of Face Recognition and Age Group Estimation

The results of face recognition and Age Group Estimation are presented in this section.

4.1.1 Face Recognition

Zhou et al. (2013) have evaluated the face recognition performance with four methods, namely LBP, Gabor+ LBP, Gabor +LPQ and Gabor +LBP+ LPQ on Yale database [27]. Table 1 presents the comparison results of the proposed work with the existing work using Extended Yale-B database under different pose and lighting conditions.

Among the four methods Gabor +LBP+ LPQ gives the best performance with the recognition accuracy of 90.70%. Moreover, according to Zhou et al. (2013) [27], among these four methods, Gabor +LBP+ LPQ is computationally intensive. ECG and LBP features showed better accuracy than either approach alone. Zhou et al. (2013) [27] obtained maximum recognition rate for LBP as 72%.

When Gabor and LBP are combined, then the recognition rate is increased to 74.7%. Accuracy of 90.7% was obtained for the combination of Gabor +LBP+ LPQ (where LPQ represent Local Phase Quantization). The proposed IPI method has a recognition rate of 98% for the combination of ECG + LBP + PCA for the Extended Yale-B database. The Recognition rate comparison is tabulated in Table 2 for different approaches using Extended Yale-B database. It can be seen that the proposed method gives the maximum recognition rate.

Table 1 Comparison of Recognition rate of the proposed work with the existing literature using Extended Yale-B database

Author	**Recognition Algorithm**	**Maximum Recognition Rate**
Zhou et al. (2013) [27]	LBP	72%
	Gabor+ LBP	74.7 %
	Gabor +LPQ	88.8 %
	Gabor +LBP+ LPQ	90.7 %
Proposed IPI method	LBP + PCA	88%
	ECG + PCA	90%
	ECG + LBP + PCA	98%

Table 2 Recognition rate comparison for different approach using Extended Yale-B database

Author	**Recognition Algorithm**	**Recognition Rate**
Feng et al. (2000) [3]	Wavelet face + LDA	84%
Harihara & Gopala Krishna (2016) [28]	HOG + SVM	88.6%
Zhou et al. (2013) [27]	Gabor +LBP+ LPQ	90.7%
Mandal et al. (2009) [29]	Curvelet face + PCA + LDA	92%
Zhou et al. (2014) [30]	PCA and logistic regression	93.33%
Proposed IPI method	ECG + LBP + PCA	98%

$$\text{Classification Accuracy} = \frac{\text{No. of Persons classified}}{\text{Total No. of Persons}} \quad (11)$$

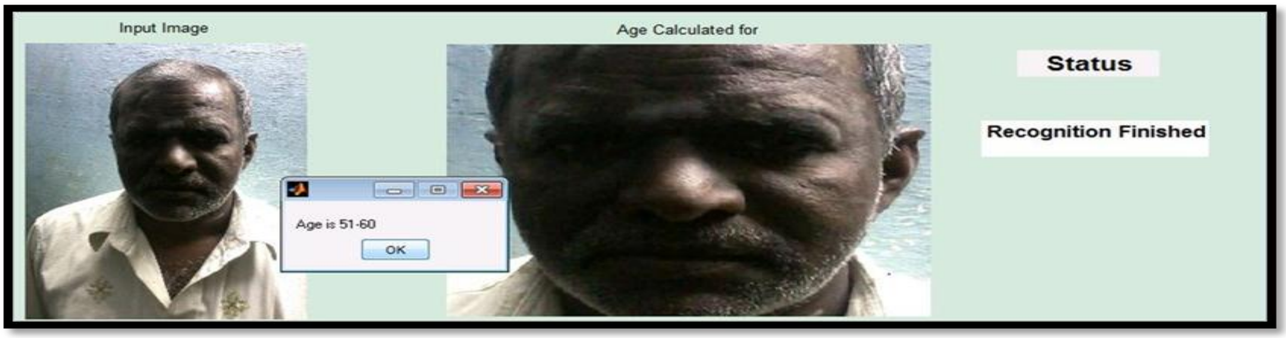
4.1.2 Results of Age Group Estimation

Experiments are also performed using the resultant fused features to estimate the age of the face using the SVM classifier. Age of the recognized face is estimated by using the extracted features of the face such as skin textures, curvature, wrinkles and skin tone. Age estimation for an individual and a group of face image is shown in Figure 9. Age of infant and older people is also differentiated and is shown in Figure 10.

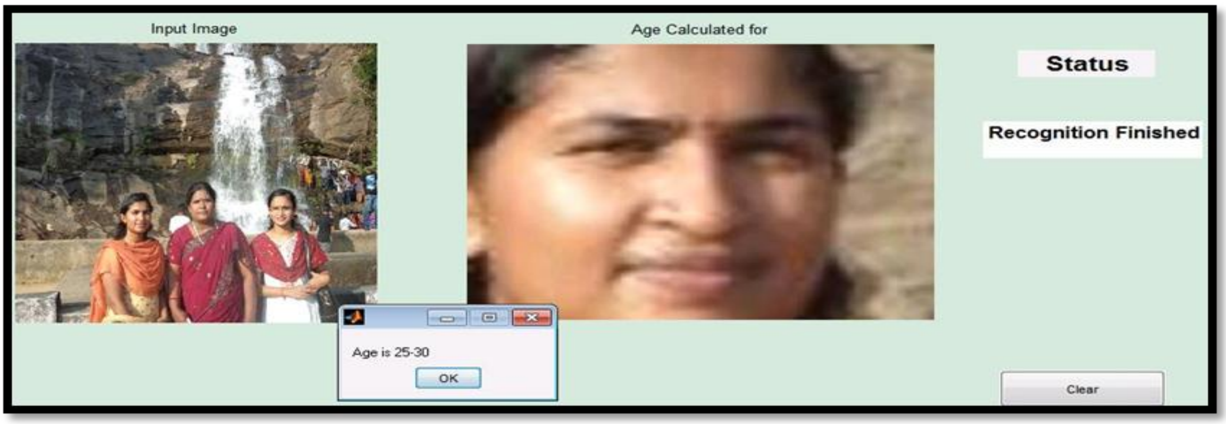
The proposed IPI methodology is evaluated using the MIT real-time database having different subjects belonging to various age groups with the different pose and lighting conditions. The proposed IPI is found to provide the correct estimation of age under various illumination and low-resolution conditions. The proposed IPI eliminates the variation due to illumination, poses and expressions for multi-variant face recognition.

5 Conclusion and Future Work

A method for face recognition under uncontrolled lighting based on robust pre-processing and complementary feature extraction is proposed. The proposed method is simple and it uses an efficient image pre-processing chain whose recognition performance is comparable to other illumination normalization methods. A heterogeneous feature fusion-based recognition scheme that combines two popular features set namely Extended Curvature Gabor wavelets and LBP is proposed for robust illumination normalization followed by PCA for dimensionality reduction. The combination of these techniques gives the state-of-the-art performance in recognition accuracy on Extended Yale-B database that contain widely varying lighting conditions, different pose, and expression. The Experiments on standard data set and real-time MIT data set show that the proposed IPI scheme is better in terms of recognition accuracy and age estimation in varying illumination, pose and low resolution.



(a) Example of an image with illumination for age group estimation



(b) Results of a group of people in an image with low resolution for age group estimation for person1

(c) Results of a group of people in an image with low resolution for age group estimation for person2

(d) Results of a group of people in an image with low resolution for age group estimation for person3

Fig. 9 Estimation of age for a single person under illumination and for a group of people with low-resolution conditions

(a) Results of a group of people in an image with younger one for age estimation

(b) Results of a group of people in an image with old person for age estimation

Fig. 10 Estimation of age for a young and old person in an image

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