LEFT AND RIGHT HORIZONTAL ELLIPTICAL TEXTURE MATRIX (LRHETM) FOR AGE CLASSFICATION

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Abstract

Age classification is one of the hot topics of the computer vision due to its applications in several fields. In the literature the age group classification is mainly carried out by the local binary pattern (LBP) based methods and methods based on the circular neighborhood (CN). The human face reflects more as elliptical structure especially mouth, eyebrows and eyes resembles more of elliptical shapes. This paper derived horizontal elliptical LBPs for age group classification. This paper found that the H-ELBP generally derives huge histogram bins thus not possible to integrate with second order statistics. This paper addressed this by dividing the base HEN into two submatirces. And based on the relative frequency code values of these two matirces this paper derived left and right horizontal elliptical texture matrix (LRHETM) for efficient age group classification. The features derive by LRHETM represents structural and statistical features. Machine learning classifiers are used for classfiction purpose. The proposed descriptor is compared with other loca based approaches on three aging facial databases. The experimental results indicates the efficacy of the proposed method over the existing popular methods of age classification.

Keywords: circular neighoborhood, elliptical shape, age group, texton.

1. Introduction

One of the crucial and important topic of human face analysis and understanding is the automatic estimation of age. The estimation of human age exactly or the estimation of the age group from human faces is known as age estimation. The exact age estimation is known as dense representation, whereas the age group estimation involves rough prediction like children; teenage; adult; middle age; old age etc. The age classification problem falls into either a multi class classification problem[1-4] or a regression problem [5-9]. The standred classifiers such as multi layer perceptron [1], adaboost [2], SVM[7, 10], k-nearest neighobors [11] are used in the literature to predict the age groups. The non-linear regression models like Gaussian process [9-12], suppot vector regression (SVG)[7, 8], quadratic regression [8] are also popular in the literature in estimating the age groups from the facial databases. The rank based approaches [13, 14, 15, 16] estimates the relative ordering information of ages more precisely, however their performance is limited. The facial age estimation is carried out by estimating wrinkles of the facial skin [17, 18, 19] and also few authors estimated the distance between facial components like eys, nose etc. The active appearance model [20] and principle component analysis (PCA) methods [21-24] are also become popular for ag group estimation. The local binary pattern (LBP) [25] is one of the most popular approaches used in many applications like texture classification [26, 28], content based image retrieval [29-31], age group classification [32, 33], face recognition [34, 35], medical image processing [36, 37] etc. The popularity of LBP is due to its 1) Extraction of significant, precise and discriminant local features 2) Rotational invariance 3) Nature of easy to understand and ease in computation. Ahone et. al [38] and Zohn et.al [39] used LBP for estimating the age groups. The methods that reduces the dimensionality [5, 40] in estimating the age groups is also studied in the literature. Several studies has proved that if the general attributes of the human face like gender [41, 42, 43], ethnicity [10-12], expression [44] are known in advances then age estimation becomes more easier and accurate. The aim of this paper is to study the elliptical or anisotropic features for age classification. Interestingly so far no researcher has studied elliptical patterns of human face for age classification.

The present paper is organized as follows: the section 1 describes the introduction. The section 2 gives detailed explanation of the proposed method. The section 3 and 4 gives the results and conclusions respectively.

2. Proposed method

Age classification (AC) plays a major role in many security and authentication issues. In the literature few models have developed on age classification. The LBP is derived on a circular or isotropic local neighborhood of 3x3. Later the LBP is extended to other neighborhood like 5x5 etc. The LBP is denoted as $LPB_{P,R}$ where P represents the number of sampling or neighboring pixels over the center pixel of the neighborhood and R represents the radius. The 3x3 neighborhood is represented with 8 sampling points P=8 and with a radius R=1 i.e $LBP_{8,1}$. The LBP based approaches are used for age classification and face recognition and this research found that they only derive isotropic structure information and they completely ignore anisotropic structure information. This is a significant finding of the present paper especially on various applications related facial databases like face recognition, age classification, recognition of pose, aging effect, recognition of mood etc because the human face represents anisotropic or elliptical shape especially the mouth, eyebrows and as age progresses the human facial surface may have more elliptical patterns and also curve patterns. From, this the present paper predicted that age groups can be easily distinguished by elliptical structures. The following Figure1 shows the circular and horizontal elliptical neighborhoods.

d_1	d_2	d_3
d_8	d_c	d_4
d_7	d_6	d_5

(a)3x3 circular LBP neighborhood

	e_1	e_2	e_3	
e_8		e_c		e_4
	e_7	e_6	e_5	

(b) 3x5 horizontal elliptical neighborhood (HEN)

Figure 1: Representation of circular and horizontal elliptical neighborhood (HEN).

From Figure1 the following points are noted down on circular neighborhood (CN) and HEN.

i. The CN requires a 3x3 window.
ii. The basic HEN requires a 3x5 window.
iii. Both the CN and HEN requires only 8 sampling points, and the sampling points d_1,d_2,d_3,d_5,d_6,d_7 and e_1,e_2,e_3,e_5,e_6,e_7 are exactly similar with respect to d_c and e_c.
iv. The e_8 and e_4 are two different sampling points of HEN when compared to CN, and d_8 and d_4 as in the case of CN.

This paper initially derived local binary patterns on horizontal-elliptical local binary patter (H-ELBP) and derived H-ELBP code (H-ELBP$_c$) in the following way as represented in equation 1 and 2.

$$H - ELBP_c = \sum_{i=1}^{i=8} 2^{i-1} * f(I(e_c) - I(e_i)) \tag{1}$$

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases} \tag{2}$$

Where I(e$_c$) and I(e$_i$) represents the intensity level of the center pixel e$_c$ and sampling point e$_i$ of the HEN. The H-ELBP$_c$ ranges from 0 to 255. The range of H-ELBP$_c$ is 0 to 2^i-1 where i is the number of sampling points of HEN. This paper replaces the center pixel value with the H-ELBP$_c$ and this process is repeated on entire image with a step length of one i.e. in an overlapped manner. This paper initially transformed the raw facial image into H-ELBP$_c$ image and histograms are derived for age classification. This approach derives a huge number of bins or features i.e. 256. The experimental results indicate satisfactory results, however not effective.

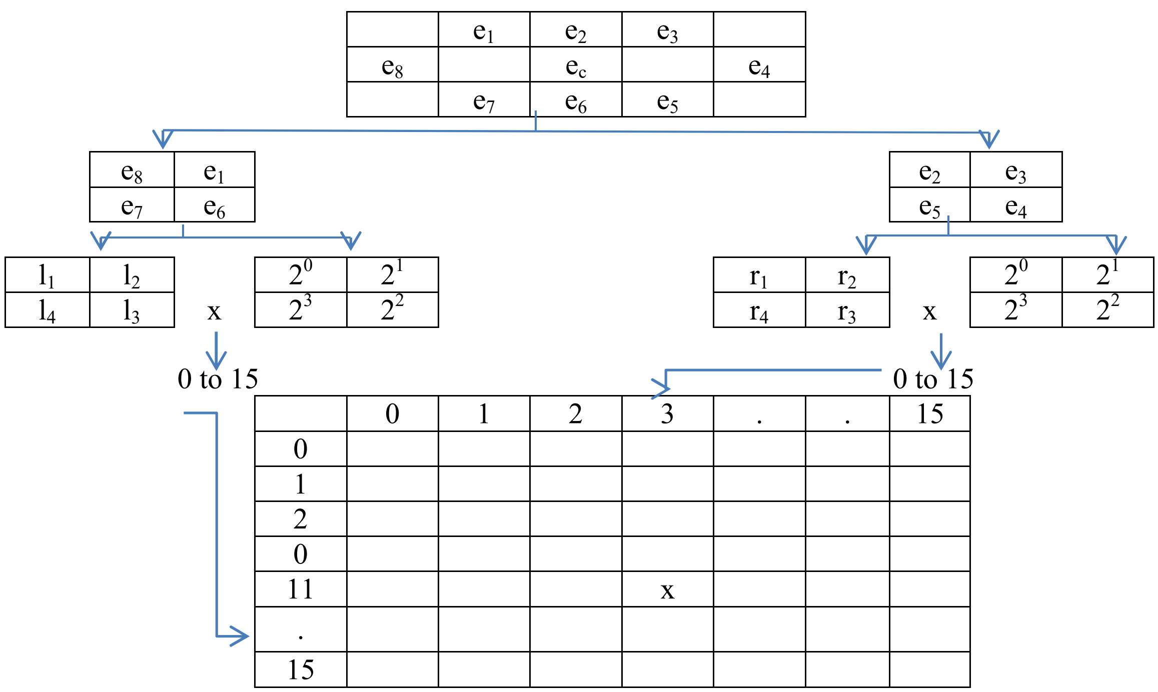

Figure 2: Frame work of the proposed LRHETM.

Further, the H-ELBP only extracts the structural information of the HEN. This paper derived a method to integrate the structural information with statistical frame work. One of the famous and popular statistical frame works is the gray level co-occurrence matrix (GLCM). The GLCM is a 2-dimensional array of gray levels or codes. The dimension of GLCM is directly proportional to the number of gray levels. The major disadvantage of GLCM is its huge dimensionality. A raw image with gray levels 0 to N-1 derives a GLCM of size NxN. The GLCM derives the spatial relationship between adjacent pixels separated by a distance d and with an angle □°.

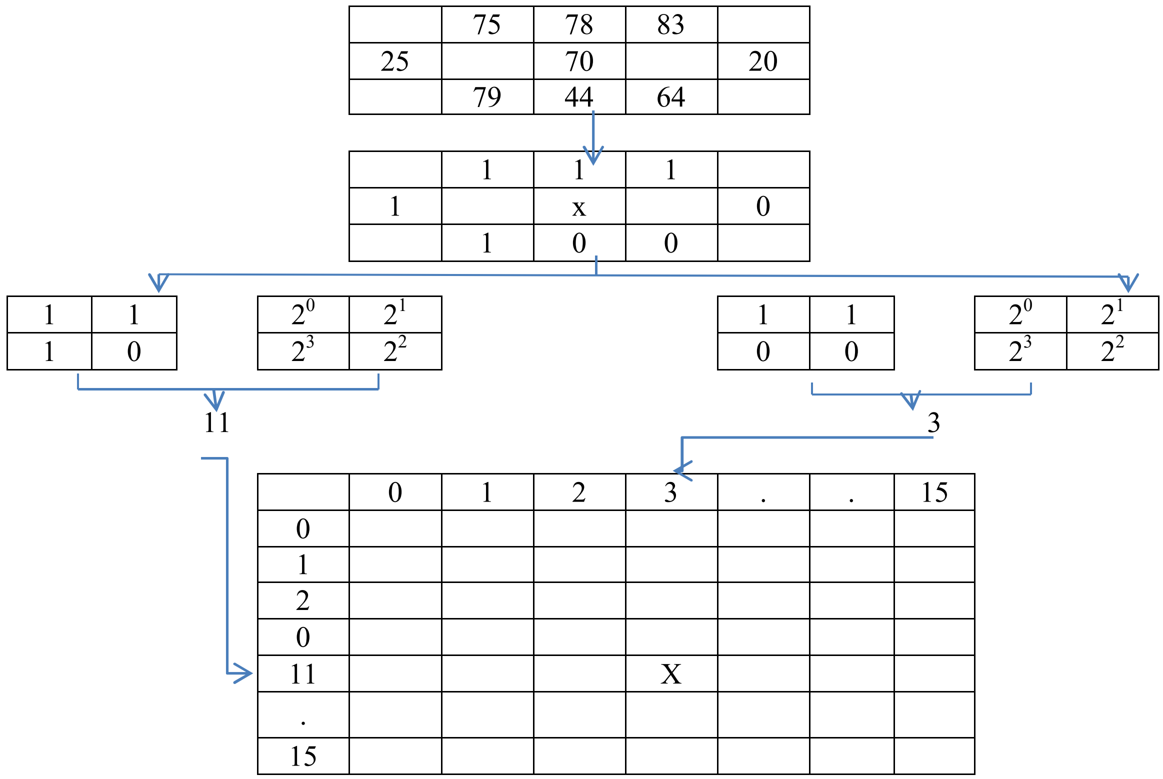

Figure 3: Derivation of the proposed LRHETM with an example.

To integrate the structural features of H-ELBP with statistical features one need to construct a co-occurrence matrix on H-ELBP code. This derives a huge matrix of size 256x256 and may not suitable for any applications. The aim of this paper is to integrate horizontal anisotropic features with GLCM features by reducing the dimensionality while preserving significant structural and statistical information for a precise age classification. For this, paper divided the HEN into two grids of size four pixels each. These grids are named as left and right matrices (Figure2). The left matrix of HEN consists of four pixels e_8, e_1, e_6 and e_7 which are left side of the center pixel e_c. The right matrix of HEN consists of four pixels e_2, e_3, e_4 and e_5 which are right side of the centre pixel e_c. The left and right matrices of HEN are named as left-horizontal elliptical matrix (LHEM) and right- horizontal elliptical matrix (RHEM) (Figure2). This paper derived binary patterns on LHEM and RHEM by comparing the gray levels of the sampling pixels with the center pixel of the HEN. Based on this left horizontal elliptical binary pattern (LHEP) and right horizontal elliptical binary pattern (RHEP) are derived and finally LHEP code ($LHEP_c$) and RHEP code ($RHEP_c$) are derived by using the following equations 3 and 4(Figure2).

$$LHEP_c = \sum_{i=1}^{4} 2^{i-1} * l_i \qquad (3)$$

$$RHEP_c = \sum_{i=1}^{4} 2^{i-1} * r_i \qquad (4)$$

Where l_i and r_i represents the binary patterns of LHEP and RHEP respectively. The l_i and r_i are derived based on the equation 2 as in the case of H-ELBP. The LHEPc and RHEPc ranged from 0 to

15. The novelty of this paper is it derived a Left and right - Horizontal Elliptical Texture Matrix (LRHETM) by measuring the relative frequencies of $LHEP_c$ and $RHEP_c$ as shown in Figure2. That is the x and y axis of LRHETM will represent $LHEP_c$ and $RHEP_c$ respectively. The dimension of LHETM will be 16x16. The LHETM measures the relative frequencies of $LHEP_C$ and $RHEP_c$ and further measures the spatial relationship between them. The proposed LHETM is shown with an example in the Figure3. This paper computes the following six GLCM features on LHETM as given in the following equations 5 to 10.

This paper derives five GLCM features as given below:

1. Contrast :

$$\text{Contrast} = \sum_{n=0}^{M-1} n^2 \left\{\sum_{i=1}^{M} \sum_{j=1}^{N} X(i,j)\right\}, |i-j| = n \tag{5}$$

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.

2. Correlation :

$$\text{Correlation} = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \frac{\{iXj\}XX(i,j) - \{\mu_x X \mu_y\}}{\sigma_x X \sigma_y} \tag{6}$$

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

3. Entropy :

$$\text{Entropy} = \sum_{i,j} \log(X(i,j).\ X(i,j) \tag{7}$$

Inhomogeneous scenes have low first order entropy, while a homogeneous scene has high entropy.

4. Homogeniety, Angular Second Moment (ASM):

$$\text{ASM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{X(i,j)\}^2 \tag{8}$$

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

5. Local Homogeneity, Inverse Difference Moment (IDM)

$$\text{IDM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \tag{9}$$

This paper performed classification of ages by using the four machine learning classifiers namely Ibk, Naviey bayes and multi-layer perceptron.

6. Prominence feature

$$Prominence = sgn\ (B)|B|^{1/4} \tag{10}$$

$$where\ B = \sum_{i,j=0}^{N-1} (i+j-2\mu)^4 P_{ij} \Big/ 4\sigma^4(1+C)^2$$

3. Results and discussions

To test the efficacy of the proposed LRHETM descriptor and to measure the age classification accuracy of the proposed method with other methods, this paper conducted experiments on three popular databases of age classification namely: FGNET [45], Google and scanned facial datasets. This paper collected 1002, 500 and 600 facial images from FG-NET, Google and scanned databases respectively. This paper derived age classification by dividing the age groups into four categories: child age group (0 to 12), young age group (13 to 30), middle age group (31 to 50) and senior age group (above 51). The sample images of these three facial databases are shown from Figure 4 to 6.

Figure 4: Sample Images of FGNET Aging Database.

Figure 5: Sample Images of Google Database..

Figure 6 : Sample Images of Scanned Photographs.

This paper computed the six GLCM features on LRHETM using the three classifiers on the representative databases and the classification results are depicted in Table 1.

Table 1: Classification rate (%) of propose LRHETM method using machine classifiers.

Age categories	Database	IBK	Multilayer Perceptron	Naïve Bayes
Childhood (0-12)	FGNET	90.21	94.21	88.21
	Google	89.21	93.26	87.62
	Scanned	88.23	93.15	86.32
Young (13-30)	FGNET	89.62	92.1	87.62
	Google	88.54	91.25	86.35
	Scanned	86.62	90.15	85.12
Adult (31-50)	FGNET	91.01	91.36	87.12
	Google	87.26	90.23	86.32
	Scanned	85.62	90.11	84.62
Senior adult (>51)	FGNET	91.32	95.23	84.62
	Google	90.52	94.23	82.16
	Scanned	90.66	93.26	81.63

From table 1, it is evident that multi-layer perceptron classifier has attained high age classification rate when compared to other classifiers. In rest of the paper this results are used especially when compared with the other exiting methods. The proposed method is compared with Horng et. al [46] , C.R Babu [47] , A Gunay [48]. Jun-Da [49], CSETM [50] , LBP[25] and H-ELBP [51] methods and results are plotted in Figure7 to Figure9.

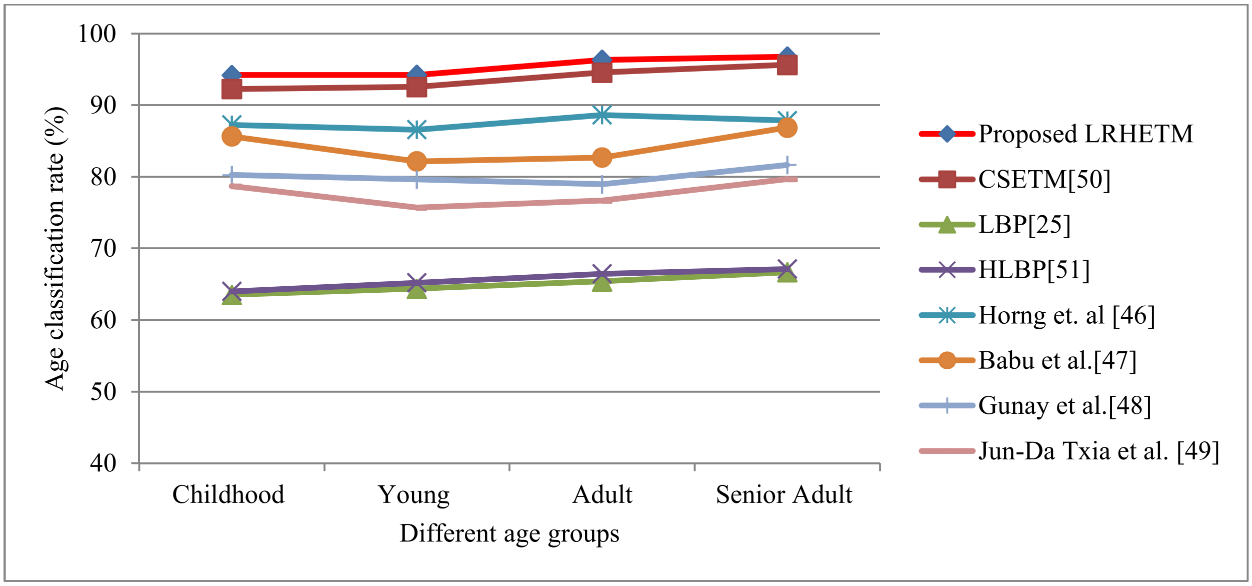

Figure 7: Age group classification on FGNET database with four categories of age groups.

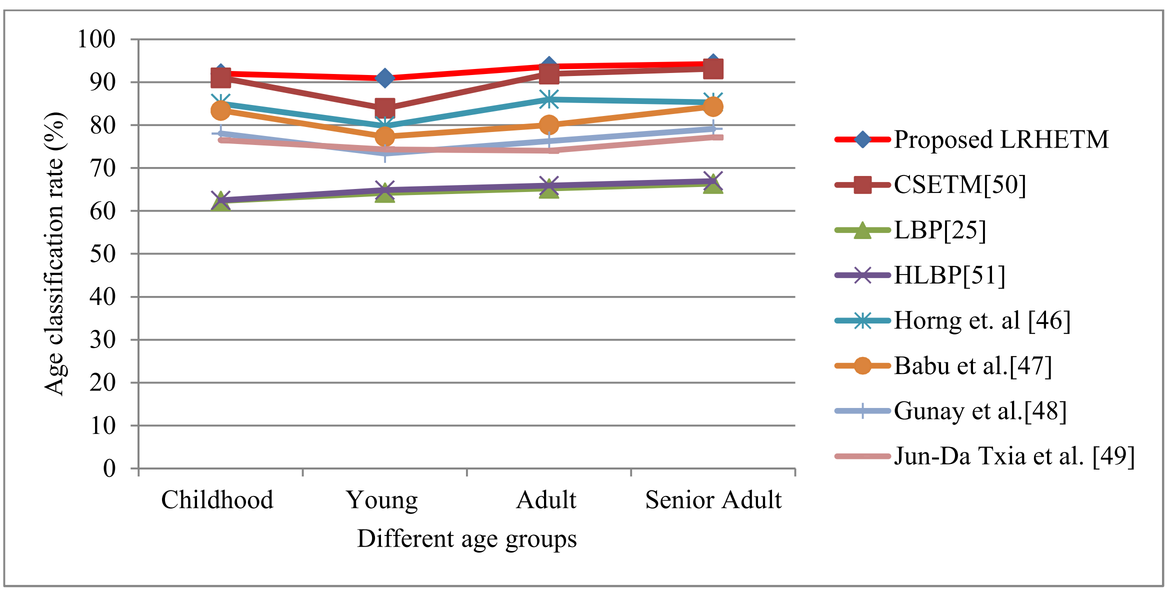

Figure 8: Age group classification on Google database with four categories of age groups.

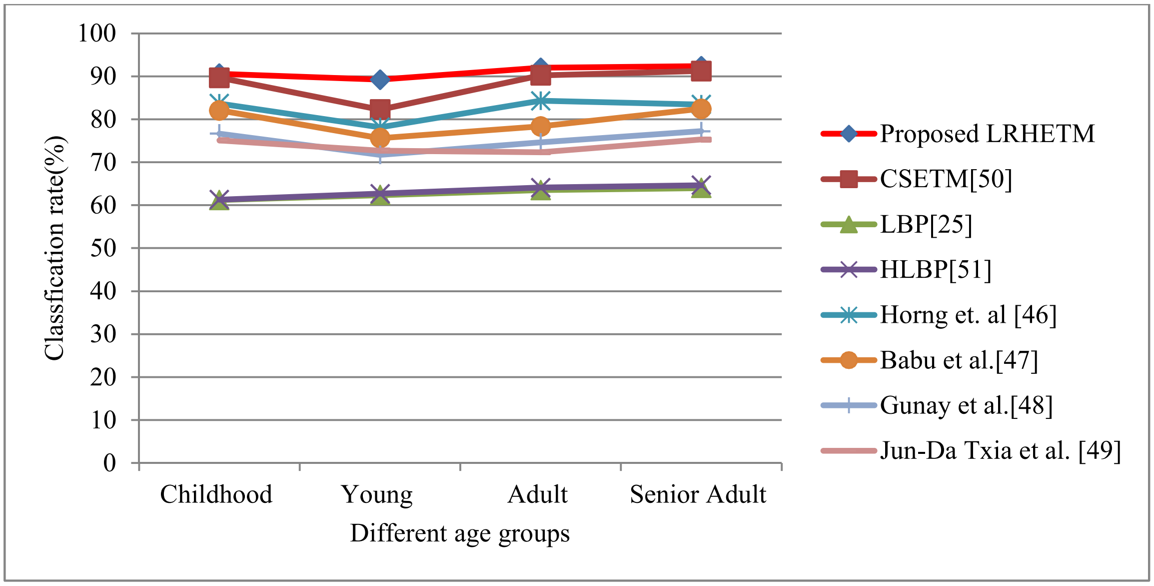

Figure 9: Age group classification on scanned database with four categories of age groups.

The main contributions of this paper are :

- Derivation of anisotropic structural information instead of isotropic structural information.
- Division of HEN of 3x5 into two sub matrices of 4 pixels each.
- Derivation of binary patterns on each of the left and right sub matrices.
- Derivation of $LHEP_c$ and $RHEP_c$ by preserving the significant elliptical features which are dominant in human face.
- Integration of LHEPc and RHEPc in the form of a single 2D matrix "LRHETM" with low dimension.
- Derivation of GLCM features on LRHETM which integrated the structural and statistical features in a more précised manner with high discriminative power.

From the experimental results the following are noted down. The proposed LRHETM attained high classification rate on all 4 age groups when compared with the above state of art methods.

1. All the existing descriptors have shown high age group classification rate on FGNET database, followed by Google and scanned facial database. The reason for this is the FGNET database was created to have minor changes in apperence as age progresses. The FGNET database is considered as bench mark database in the age group classification by researchers. The clarity of human faces on scanned databases is slightly poor when compared to other two databases.
2. The LBP has attained a poor age classification result on all database. The main reasons for this are due to i. Huge number of histogram bins ii) Ignoring the anisotropic or elliptical structural information; by nature LBP is a circular structure iii) Not having any integration with statistical parameters.
3. The H-ELBP attained satisfactory classification results, however the results are for less when compared to the proposed LRHETM the main reason for this is the non integration of H-ELBP with statistical parameters this is mainly due to the huge histograms of H-ELBP.
4. The significant results is the H-ELBP has attained an improvement over LBP. This clearly proves that the anisotropic structural information is capable of capturing more information regarding the estimation of ages.

5. The proposed LRHETM attained high classification rate when compared to other state of art existing methods: the main reasons are derivation of anisotropic information instead of isotropic information and integration of this with co-occurrence matrix and computation of GLCM features.

6. The left and right horizontal elliptical texture matrix (LRHETM) attained high age classification rate on the age group: senior adult and child hood. The other two age groups attained 1 to 2% of low age classification rate when compared to childhood and senior adult. The reason for this the proposed features of LRHETM are more matured on these two age groups: senior adult and childhood.

Further, this paper observed the following by carefully looking into mis-classification results especially the overlapping of classification results from one category of age group to the other.

1. There is an overlap of age misclassification between child and young age groups.
2. Interestingly child age has no overlappeing or misclassification with other age groups.
3. There is a very narrow misclassification of age groups between young and middle age groups.

This paper also experimented by dividing the facial images into three age groups 1) childhood from the age 0 to 21 2) young and middle age group 22 to 49 3) Senior age group from 50 years onwards.

The age classification rates of the proposed descriptors based on three age groups on three databases using multi-layer perceptron and also the classification rate of the other existing methods are plotted in the form of graphs from Figure10 to Figure12 and it is observed that the overall age classification rate is improved with less number of age group classifications. The proposed method outperformed the other existing databases.

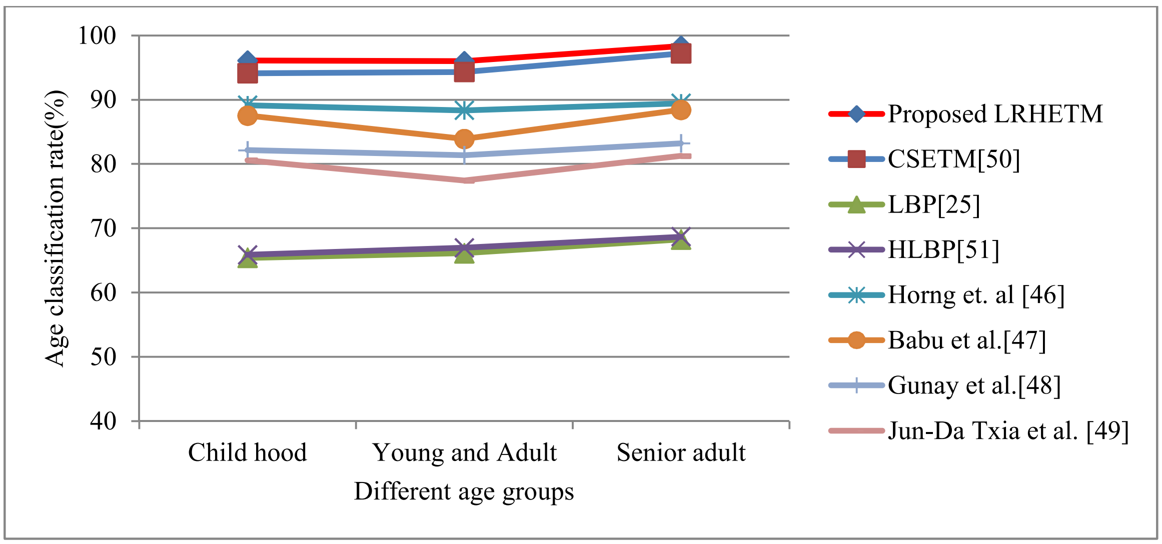

Figure 10: Comparison of proposed and existing method in terms of age group classification rate on FG-NET database with three categories.

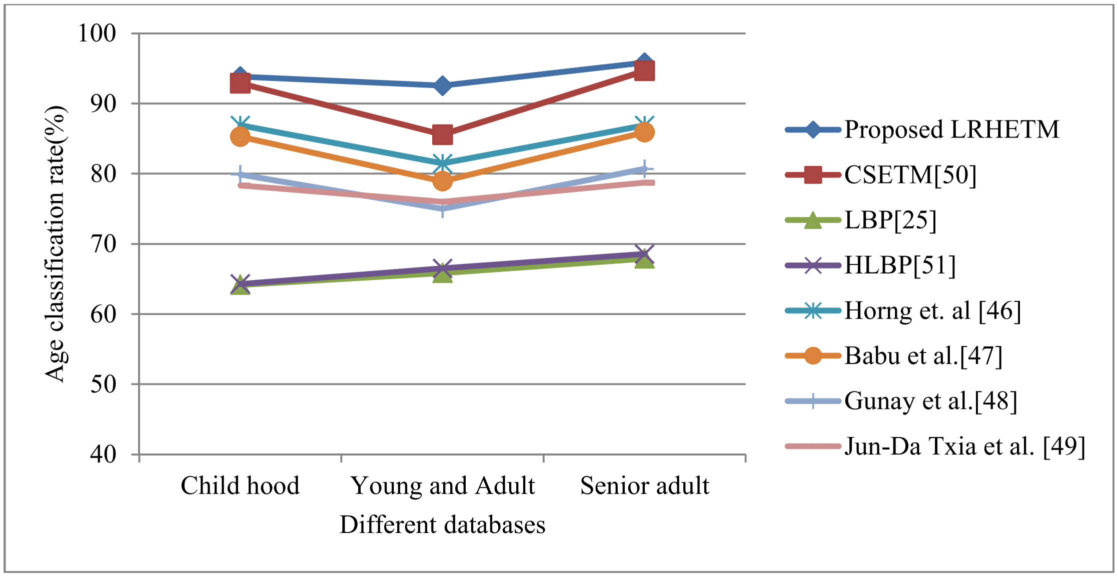

Figure 11: Comparison of proposed and existing method in terms of age group classification rate on Google database with three categories.

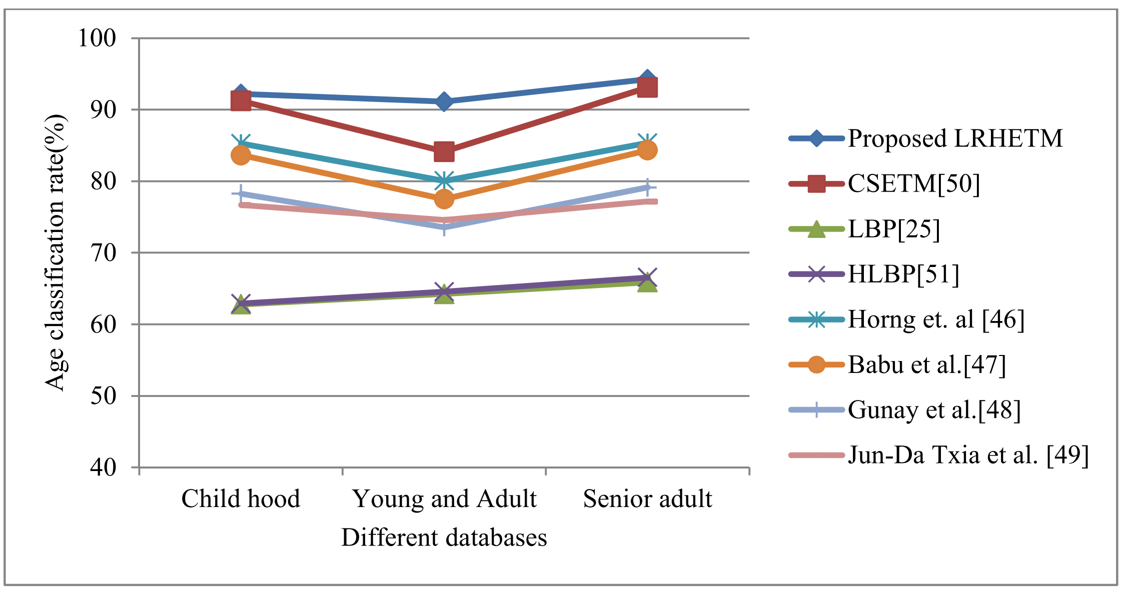

Figure 12: Comparison of proposed and existing method in terms of age group classification rate on scanned database with three categories

4. Conclusions

This paper derived a new classical approach for age group classification by deriving elliptical structures information on facial images. The human face resembles more or like elliptical structure and as the age group progresses, there will be more numbers of elliptical curve patterns on human face. This novel approach draw good results on H-ELBP when compared to LBP as evident in the graphs. The division of HELBP into 2 sub matrices and computing relative frequencies of each matrix and deriving a co-occurrence matrix based on this, the present paper derived LRHETM. The six GLCM features derived on LRHETM exhibited structural and statistical feature, thus the proposed

LRHETM exhibited a high age group classification rate. This paper used machine learning classifiers for classification of age groups. The experimental results on various facial databases clearly proves the efficacy, robustness and compactness of the proposed LRHETM over the exiting state-of-art age classification methods.

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