Age Classification Based On Appearance Model Using Local Ternary Direction Pattern Approach

Nara Sreekanth ,Munaga HM Krishna Prasad

Abstract*: *The appearance model play a vital role in many applications related to facial images. This paper derives a new approach of appearance model using local ternary derivative patterns on human facial images for effective age groups classification. In the literature direction patterns are derived with respect to central pixel of the neighborhood. This paper derives ternary direction patters (TDP) between sampling points of the neighborhood with a strong assumption that the relationship between adjacent pixels derive rich information. This paper divides the neighborhood into vertical and horizontal units and derives the TDP and based on the relative frequencies of horizontal and vertical TDP, this paper derives horizontal vertical direction unit matrix (HVDUM). The gray level co-occurrence matrix (GLCM) features are derived on HVDUM for age classification and the experimental results are compared with the existing methods and the results indicate the efficiency of the proposed method over the existing methods.

Keywords: neighborhood; vertical-horizontal units; GLCM features; sampling points

I. INTRODUCTION

The methods derived for image analysis, segmentation and object recognition plays a major role in facial image classification and also in age classification problems. The class of facial methods includes i) Age classification ii) Age group estimation iii) Face recognition iv) Facial expression recognition v) identification of mood of a person etc. These methods have various commercial and security applications: smart cards; driving licenses ; credit and debit cards; registration of properties ; biometric authentication; restaurants and in clubs ; law enforcement; passports etc. Due to the above applications in recent days tremendous interest have been shown by many researchers in academic and in industry on methods based on facial images. Human face provides a rich amount of significant information which is crucial in many interesting applications as mentioned above. Inspired by these applications many researchers derived a diverse set of methods; however most of them are based on local features. However, still lot of work is needed in deriving age classification methods that are suitable to real time applications or real time scenarios. Though the human face provides a good amount of information however the appearance of a face varies due to change in expression, pose, and illumination and due to other factors like make-up, occlusions etc.., and this affects the age classification process. Therefore finding a universal classification model for human faces is a troublesome or crucial task. How to perceive human faces and how to model the distinctive features of human faces are the challenges faced by the researchers in computer vision and psychophysics researchers. Human face is considered to be a special class of 3D objects. As age grows there will be variations in human face [1]. The face recognition and identification models are significantly affected by variations in appearance due to age [2]. The age classification reduces the complexity of face identification by sorting the database images by age groups. The age group of the query facial image is computed initially and the query image is matched with those images of the database that falls under the query image age group. This will reduce the identification time. If the database images are not divided by age wise than the query image has to be compared with all the images of the database. The age classification is one of the challenging and interesting problems due to the anatomic changes in the crania-facial region, the bony portion of the head and overlying soft-tissue caused by the aging progress [3]. The classification of age on human faces can be divided into three categories: i. age group classification [4, 5, 6, 7], the hierarchical age estimation [8, 9] and exact or single-level age estimation [10-13]. In 1999 based on local features i.e. by extracting wrinkles on facial images age group classification is carried out [14]. Age is classified into three groups: babies, young adults and seniors by known and lobo [14]. Later in 2006 a classifier based on 2D-LDA approach is proposed for age groups classification and this method exhibited robustness under varying lighting conditions. The facial image features can be described in two ways: geometric-feature based and appearance feature-based methods [15]. The geometric-feature- based methods encodes the relationship between main components of facial image: eyes, mouth, nose etc.[16-23]. These methods [16-23] are invariant to scale and rotation. The main disadvantage of these methods is they depend on exact locations of the facial components and they are difficult to locate under various appearances [24]. The appearance based methods can overcome this. The appearance model represent facial images by using filters, which can be applied on the whole image (holistic features) or on the specific region of the face (region based) or on the specific local component (local feature). In the literature there are many holistic methods of appearance model: Eigen faces [25], Fisher faces [26], 2D principal component analysis (PCA) [27], local directional analysis [LDA] [28] and IDA [29].

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Nara Sreekanth, Research Scholar - Rayalaseema University (Research Scholar – PP.COMP.SCI.0303), Associate Professor, Dept of C.S.E, BVRIT Hyderabad college of Engineering for women, Bachupally, Telengana, India

Munaga HM Krishna Prasad , Professor, Department of Computer Science and Engineering, University College of Engineering Kakinada, JNTUK, Pithapuram Road, Nagamallithota, Kakinada, Andhra Pradesh, India

Though holistic approaches have shown promising results, however they exhibited poor results under illumination variations. To address this local based appearances models on facial images are derived and the popular local based facial appearances models include: local binary pattern (LBP) [30-31], local phase quantization (LPQ) [33], local directional neighborhood (LDN) [34, 35], HOG[36] and local ternary pattern (LTP) [37].

The advantage of the above local based approaches is [30-37] they can accommodate local variations easily than holistic based approaches. The edge based and histogram based local approaches [33-36] extracted significant features of the facial image. This research observed that the local based methods extracted significant features; however they have derived huge histogram bins and that's why they are unable to integrate with statistical features. To address this, this paper derives local features and adopted a method to reduce the bin size by dividing the neighborhood into dual neighborhood and thus integrating with statistical features for efficient age classification.

This paper is organized as follows: the section one describes the introduction, the section two describes the proposed method, the section three and four presents the results and discussions and conclusions respectively.

II. PROPOSED METHOD

The local based methods like local binary pattern (LBP) and its variants extracted significant local features by extracting a relationship among each sampling point over central pixel of the circular neighborhood. The other structural local based methods like elongated local binary pattern (ELBP) followed the same suite in extracting the local features. The pixel is the fundamental unit of the image texture. This paper strongly believes that the relationship between adjacent pixels derives more meaningful information. Based on the relationship between adjacent pixels in the literature many edge operators, morphological operators and other operators are defined. These operators are playing a crucial role in many image processing applications. Based on this, this paper derives two types of derivative relationships between adjacent set or sampling set of pixels on a 3x3 neighborhood.

The Fig.1 (a) shows a 3x3 neighborhood with 8-sampling points designated as $V_1,V_2,V_3,V_4,V_5,V_6,V_7$ and V_8 and the center pixel of the neighborhood is denoted as Vc. The LBP estimated the binary relationship between center pixel and each of its sampling points and derived a unique LBP code (LBPP,R) for the center pixel. The LBP code replaces the gray level value of the center pixel with LBP code and this process is repeated on entire image thus the image will be transformed into a LBP coded image (Eqn.1 and 2)

$$LBP_{8,1} = \sum_{i=1}^{8} 2^{i-1} * f(V_i - V_c) \quad (1)$$

$$where\ f(x) = \begin{cases} 1, & if\ V_i \geq 0 \\ 0, & Otherwise \end{cases} \quad (2)$$

V_1	V_2	V_3
V_4	V_c	V_5
V_6	V_7	V_8

(a) A 3x3 neighborhood

V_1	V_2	V_3
V_6	V_7	V_8

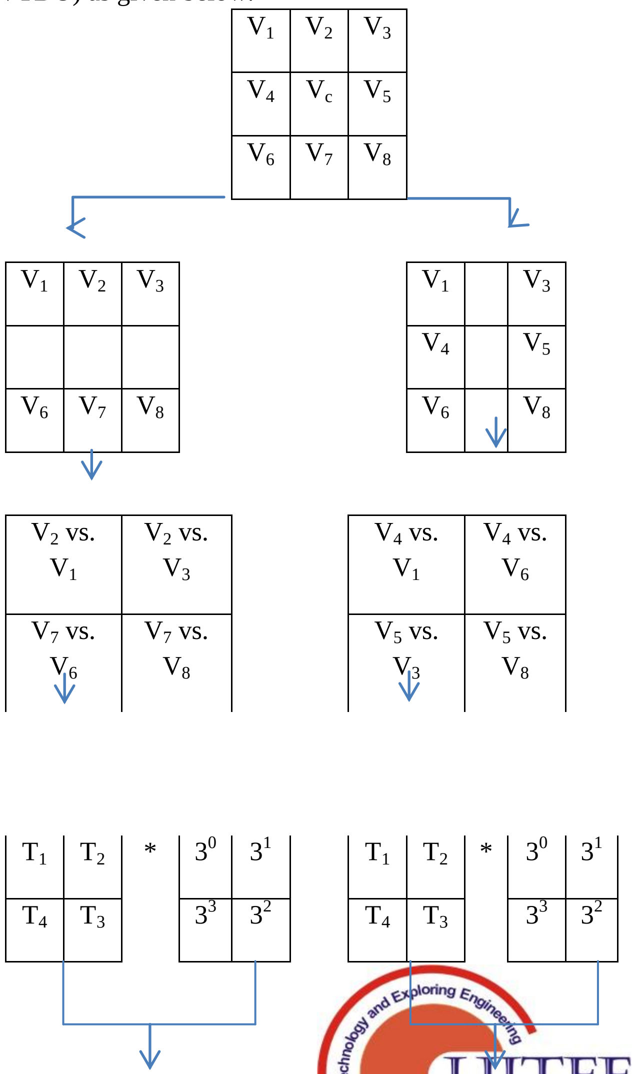
((b) Horizontal unit (HU)

V_1		V_3
V_4		V_5
V_6		V_8

(c) Vertical unit (VU)

Fig.1: A 3x3 neighborhood with horizontal and vertical units.

This paper initially divides the facial image into micro regions of size 3x3 in a non-overlapped manner. Each 3x3 neighborhood is divided into two grids: horizontal and vertical grids as shown in Fig.1 (b) and 1(c) respectively. This paper derives ternary direction vectors (TDV) between two pixels of horizontal and vertical units by comparing the grey levels of the adjacent pixels. This paper is different from LBP approach and computes the ternary direction vector between central pixel of a row or column with its neighboring pixels. The cross pixels of a 3 x 3 neighborhood are treated as the central pixels of a row or column among the sampling points of the neighborhood. This paper derived a ternary direction relationship in between sampling points of HU and VU. This paper derived four sets of relationship between V_2 vs. V_1; V_2 vs. V_3; V_7 vs. V_6; V_7 vs. V_8 on HU and V_4 vs. V_1; V_4 vs. V_6; V_5 vs. V_3; V_5 vs. V_8 on VU. Based on this relationship this paper derived horizontal ternary direction unit (HTDU) and vertical ternary direction unit (VTDU) as given below.



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$HTDU_c$ = { 0 to 80} $VTDU_c$ = { 0 to 80}

Fig.2: Frame work for the derivation of HTDUc and VTDUc.

The ternary relationship is derived based on the following equation 3

$$if\ (V_i) > (V_j) then\ T_i = 0 \quad (3)$$

$$if\ (V_i) == (V_j) then\ T_i = 1$$

$$else\ \ T_i = 2$$

The HU and VU derive a total of 4 sets of horizontal ternary patterns (HTDP) and vertical ternary patterns (VTDP) (Fig.2). This paper derived horizontal ternary direction unit code (HTDUc) and vertical ternary direction unit code (VTDUc) by multiplying HTDP and VTDP with ternary weights (Fig.2). This results a unique code ranging from 0 to 80 for HTDU and VTDU. The process of generation of HTDUc and VTDUc on a 3x3 neighborhood is shown in Fig.3.

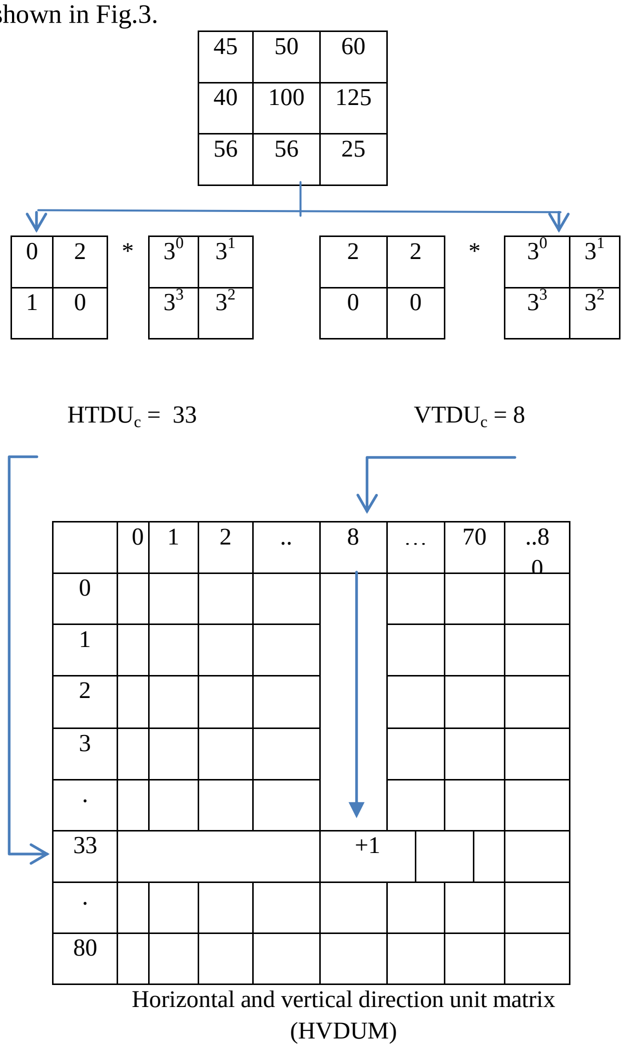

Fig. 3: Generation of HVDUM from the 3x3 neighborhood.

This paper derived horizontal and vertical Direction unit matrix (HVDUM) using the relative frequencies of the HTDUc and VTDUc. The relative frequencies measure the derivative ternary patterns of horizontal and vertical units of the 3x3 neighborhood. The HVDUM is a 2-D matrix that consists of HTDUc on row side and VTDU on the column side. Each entry of the HVDUM measures the frequency occurrences of the relative frequencies (i,j) of the HTDUc and VTDUc. This paper derived gray level co-occurrence matrix features on HVDUM. The dimensions of HVDUM will be 81 x 81. This paper computes four HVDUMs with varying distances 'd' rages from 1,2, 3 and 4. On each distance value this paper computed HVDUM with four different angles 00,450,900 and 1350. This results a total of 16- HVDUM and four HVDUMs on each distance value d. The six GLCM features are derived on each angle of rotation. This paper computed the average feature value on each distance value and this is considered as feature value of the di. The process of derivation of GLCM with gray level range 0 to 3 for 00,450,900 and 1350 are shown in Fig. 4

0	2	3	1	2
0	2	1	3	1
2	3	3	2	1
3	1	0	1	2

0^0	0	1	2	3
0	0	1	2	0
1	1	0	2	1
2	0	2	0	2
3	0	3	1	1

45^0	0	1	2	3
0	0	0	2	0
1	0	2	0	1
2	0	1	1	1
3	0	1	1	2

90^0	0	1	2	3
0	1	0	0	0
1	0	1	2	2
2	1	1	1	1
3	0	2	2	0

135^0	0	1	2	3
0	0	0	0	1
1	0	1	2	2
2	1	1	1	0
3	1	0	1	1

Fig. 4: Derivation of Co-occurrence matrix in four directions (00,450,900 and 1350).

This paper computed the following 6 gray level co-occurrence matrix (GLCM) features on the HVDUM to extract facial features for the age classification.

Contrast :

Contrast $\sum_{n=0}^{M-1} n^2 \left\{\sum_{i=1}^{M} \sum_{j=1}^{N} X(i,j)\right\}, |i-j| = n =$ (4)

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

Correlation :

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$$\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{\{iXj\}XX(i,j)-\{\square_x X \square_y\}}{\sigma_x X \sigma_y} \quad (5)$$

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

Entropy :

$$\text{Entropy} = \sum_{i,j}\log(X(i,j).\ X(i,j) \quad (6)$$

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

Angular Second Moment (ASM):

$$\text{ASM}= \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{X(i,j)\}^2 \quad (7)$$

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)

$$\text{IDM}= \sum_{\mathrm{i}=0}^{\mathrm{G}-1}\sum_{\mathrm{j}=0}^{\mathrm{G}-1}\frac{1}{1+(\mathrm{i}-\mathrm{j})^2}\mathrm{P(i,j)} \quad (8)$$

6. Prominence feature

$$Prominence = sgn\ (B)|B|^{1/4} \quad (9)$$

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

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

III. RESULTS AND DISCUSSIONS

To test the efficacy of the proposed 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 [38], 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 Fig. 5 to 7. The proposed HVDUM is experimented with four distance values ‘d’ i.e. d=1,2,3 and 4 and on each d value computed the six GLCM features for different rotations 0o,45o,90o and 135o. the average value of a feature vector of all rotations of a distance value di considered as the feature vector. The six average feature vectors computed on the proposed HVDUM for each di is given to machine learning classifiers Ibk, Naivebayes and multilayer perceptron. All the three classifiers has shown high age group classification for d value equal to 2 and the classification rates are given in Table 1 for d value equal to 2.

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Fig. 5: Sample Images of FGNET Aging Database.

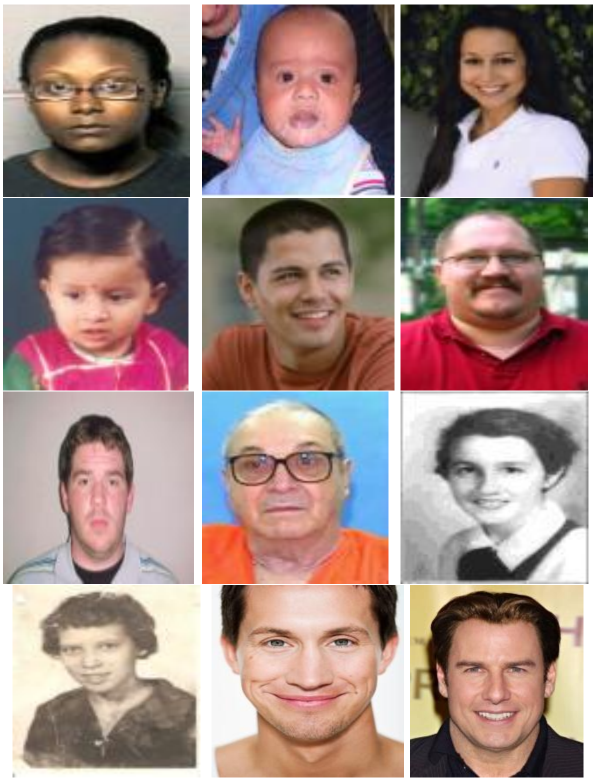

Fig. 6: Sample Images of Google Database.

Fig.7 : Sample Images of Scanned Photographs.

The average six GLCM features vectors computed on the proposed HVDUM for each di is given to machine learning classifiers IBK, Multilayer Perceptron, and Naïve Bayes. All the three classifiers has shown high age group classification rate on all considered databases for d value equals to 2 and the age group classification rate for di=2 is given in table 1.

Table 1: Age group classification rate (%) of proposed HVDUM method using machine classifiers for di=2.

Age categories	Database	IBK	Multilayer Perceptron	Naïve Bayes
Childhood (0-12)	FGNET	91.56	95.63	89.47
	Google	90.56	94.68	88.88
	Scanned	89.58	94.57	87.58
Young (13-30)	FGNET	90.97	93.52	88.88
	Google	89.89	92.67	87.61
	Scanned	87.97	91.57	86.38
Adult (31-50)	FGNET	92.36	92.78	88.38
	Google	88.61	91.65	87.58
	Scanned	86.97	91.53	85.88
Senior adult (>51)	FGNET	92.67	96.65	85.88
	Google	91.87	95.65	83.42
	Scanned	92.01	94.68	82.89

From table 1, it is evident that multi-layer perceptron classifier has attained high age classification rate on HVDUM descriptor when compared to other classifiers. In rest of the paper this results are used especially when compared with the other exiting methods.

The proposed HVDUM method is compared with Horng et. al [39] , C.R Babu [40] , A Gunay [41]. Jun-Da [42], CSETM [43] , LBP[44] and H-ELBP [45] methods on three facial datasets and results are plotted in Fig.8 to Fig.10.

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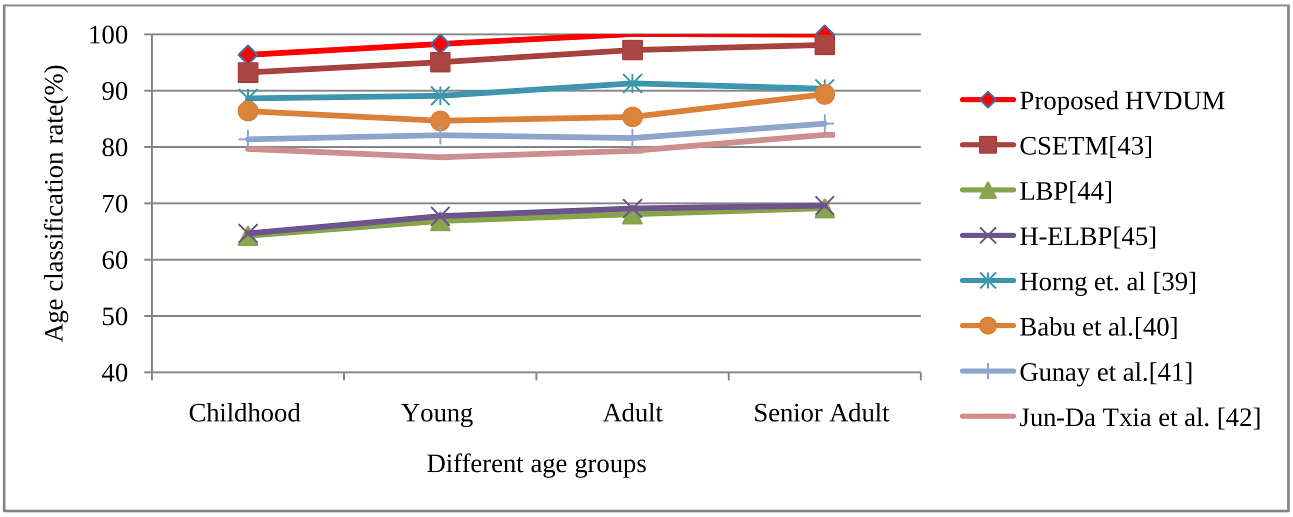

Fig. 8: Age group classification on FGNET database with four categories of age groups.

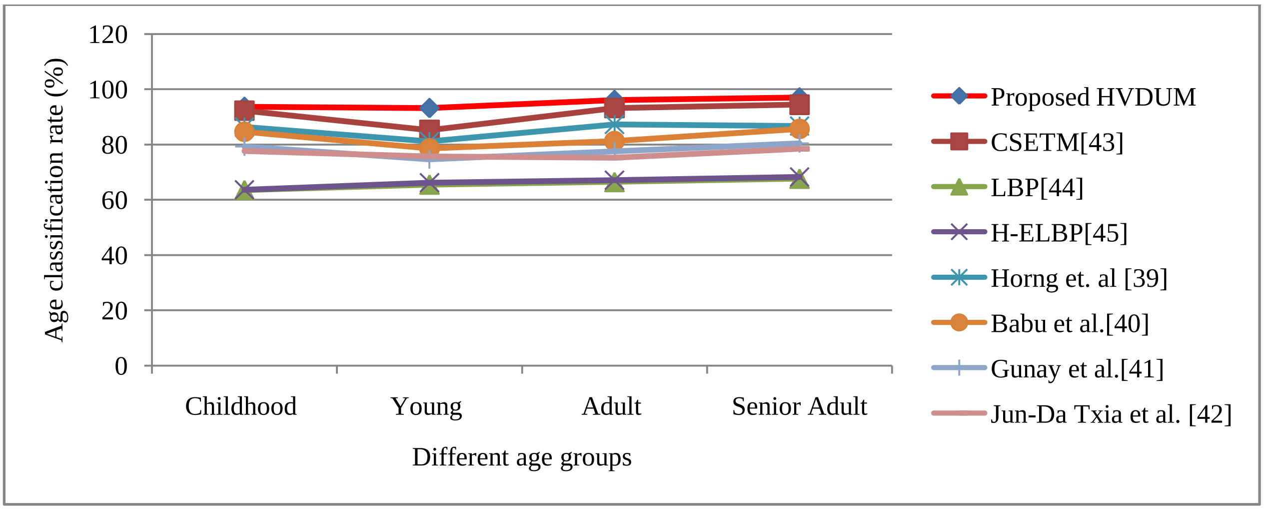

Fig. 9: Age group classification on Google database with four categories of age groups .

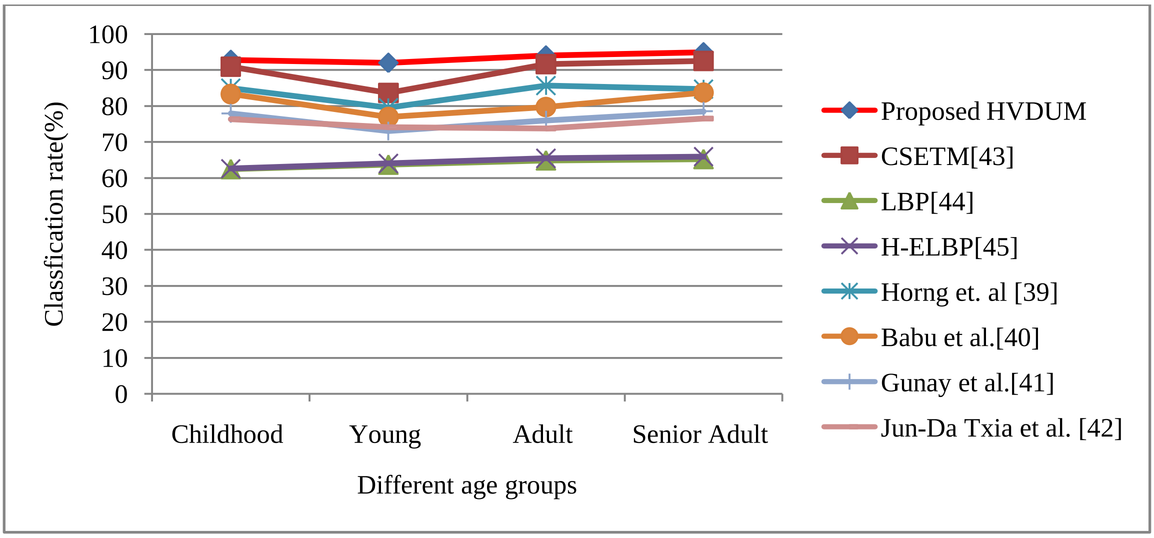

Fig. 10: Age group classification on scanned database with four categories of age groups.

The main contributions of this paper are:

- Derivation of significant features among the adjacent pixels of the sampling points of a neighborhood.

- Derivation of ternary direction vectors instead of binary patterns.
- Computation of HTDUc and VTDUc that preserves the significant facial features.
- Derivation of HVDUM descriptor with low dimensionality based on the relative frequencies of HTDUc and VTDUc.
- Derivation of GLCM features on HVDUM which integrated the local direction patterns of sampling points with statistical features in a more précised manner with high discriminative power and low dimensionality.
- Feature extraction by integrated local features and classification by machine learning classifiers.

From the experimental results the following are noted down. The proposed HVDUM exhibited a good improvement in age group classification when compared to the other state of are local based methods.

The age group classification on facial data base wise: The FGNET followed by Google and scanned facial database have shown good age group classification rate on all the proposed method and existing methods. Out of these three databases the FGNET attained a high age group classification rate since the FGNET database was created to have minor changes in appearance 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.

Due to huge histogram bin size; ignoring the directional vectors; not having any integration with statistical parameters, the LBP has exhibited a poor age group classification rate. When compared to isotropic structural features of LBP the anisotropic structural features of HELBP attained a little improvement. When compared to other existing descriptors the proposed HVDUM attained a high face recognition rate the main reasons are i) the derivation of relationship between sampling points instead of central pixel and each sampling point. ii) the derivation of ternary direction pattern iii) integration of direction patterns with GLCM features.

Further, this paper observed the following by carefully looking into miss-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 overlapping 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 Fig.11 to Fig.13 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.

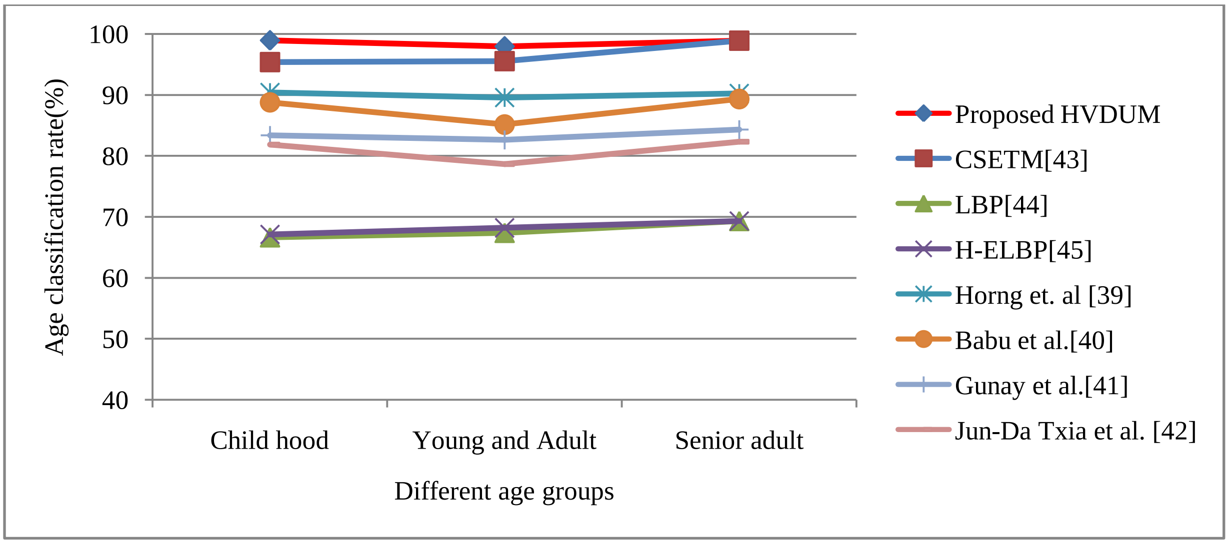

Fig.11: Comparison of proposed and existing method in terms of age group classification rate on FG-NET database with three categories.

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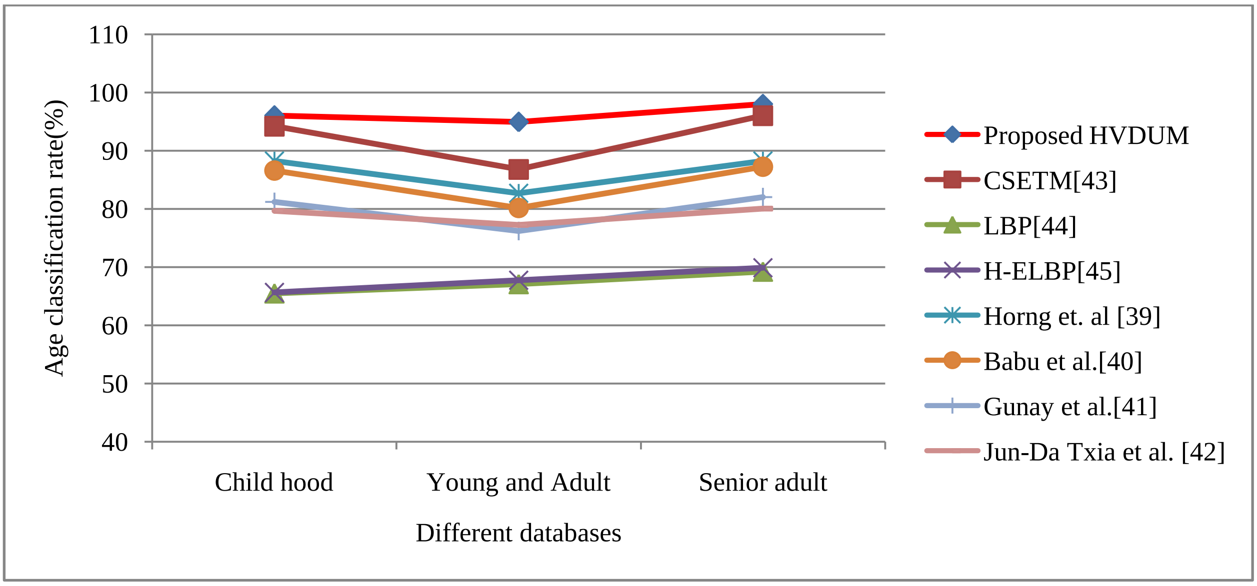

Fig. 12: Comparison of proposed and existing method in terms of age group classification rate on Google database with three categories.

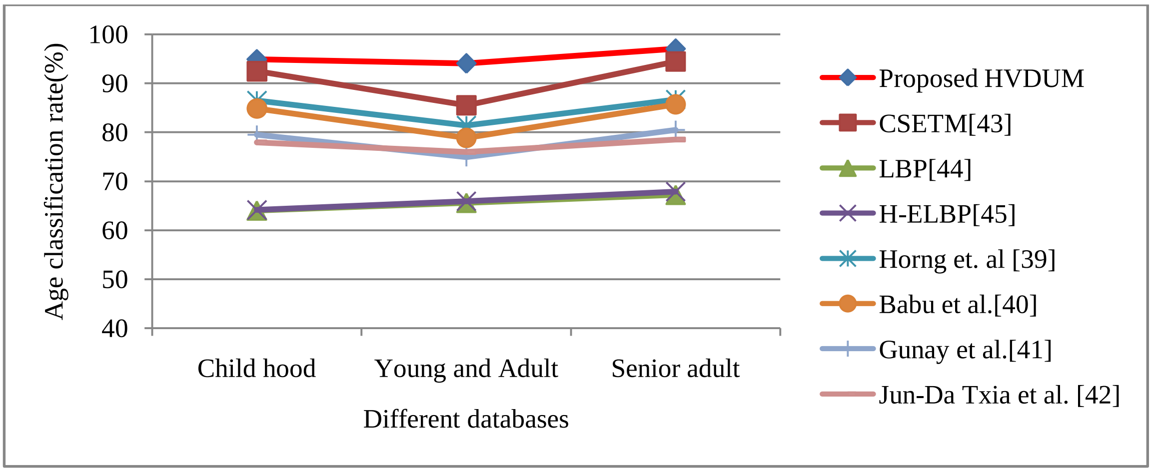

Fig. 13: Comparison of proposed and existing method in terms of age group classification rate on scanned database with three categories

IV. CONCLUSIONS

This paper derived a new classical approach for age group classification by deriving directional information on facial images. The directional pattern derived on sampling points is a new approach and it can be applied to the variety of applications. The division of sampling points in to two units and derivation of ternary relationship between cross sampling point's verses rest of the sampling points derived two types of ternary direction codes i.e., HTDUc and VTDUc. The novelty of this paper is the derivation of HVDUM from the HTDUc and VTDUc. The derivation of GLCM features on HVDUM integrated the structural features and ternary direction patterns with statistical features of facial images for an effective age classification. The proposed descriptor exhibited a high age classification rate when compared to the other existing local descriptor with low dimensionality. The experimental results on various facial databases clearly prove the efficacy, robustness and compactness of the proposed HVDUM over the exiting state-of-art age classification methods.

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