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Region Based Age Classification using Cross Diagonal Centre Symmetric Motif Matrix (CD-CS-MM)

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Abstract*: *Age group classification of human beings based on their facial images plays a vital role in many application including security, low and enforcement etc… The extraction of significant features from the facial textures plays a crucial role in age classification. The precise and significant features from facial images can be derived based on local, region or global based methods: out of which local based methods exhibits good results. This paper derived the facial features from local and macro regions. This paper initially divided the facial image into micro regions of size 2x2. The Motifs are derived on each 2x2 grid and the grid is replaced with Motif coded image. This paper divides the image into micro region of size 3x3, where each value represents a Motif index value of a 2x2 grid. This research derives centre symmetric relationship and also measured the cross and diagonal relationship between the Motif codes. This transforms the image into a cross diagonal centre symmetric Motif coded image (CD-CS-MC) image where the code ranging from 0 to 31. The gray level co-occurrence matrix (GLCM) features are derived by deriving a co-occurrence matrix on CD-CSMC and these results a CD-CS-Motif Matrix (CD-CS-MM). The CD-CS-MM is tested on popular facial databases and tested with by dividing the age groups into 4 and 3 levels. The experimental results reveal the efficacy of the proposed method over the other methods.

***Index Terms*: Texture, Motif, micro region, texture, GLCM.**

I. INTRODUCTION

The development and innovations in human machine interaction systems led a major role in the development and creation of numerous face identification models [1-4]. A facial application system is trained by using a large number of facial images and with large number of facial features derived on each face. To achieve high identification rate of human faces the derived feature must be tolerable to intro-individual variations in facial appearance. Aging variation is treated as an intra-individual variation of human faces which is not investigated in depth face recognition system, during the design and testing process. As age changes, it derives a significant alteration in human face. In fact the process of aging causes the dominant changes in the appearance of face and anatomy. This results a gradual change in overall metamorphosis of a human face into a difference face. Even the appearance of facial components (like eyes, eye brows, nose, mouth, chin etc) may be distorted and this results in the deterioration of the ability of recognition by the human-face interaction systems in identifying the individual with different ages. The age classification system can be used in many applications:

1. Prediction of facial appearance of missing individual or wanted individuals. These methods predict the facial structure and appearance of the missing persons based on the facial image they have. These are known as prediction systems missing children in the literature are semi-automatic age progression systems [7-9, 10].
2. Updating records: these systems have to automatically update the faces which are on the records so that the current appearance of the corresponding of face will be always preserved. The advantage of this aging system is the face recognition system will be more accurate and it overcomes the need of replacing or updating the facial data manually which is a tedious process.
3. The current research encountered the following difficulties in aging process diversity of aging variations which may be different from persons to persons. Aging variation can be affected by external factors such as health, expose to external weather conditions, standard of living etc: the difficulty in collecting the training data periodically. In the literature statistical face models [11, 12] are proposed to derive reversible coding on facial images. In the literature automatic face processing [1-4] models are proposed to extract automatically the facial features.

In the literature Thompson [13] suggested of model for estimating the shape of biological system by using co-ordinate transformation. Based on this idea [13], many researchers in the literature attempted to derive age related changes of human face [14, 15] based on co-ordinate transformation. These researchers [14- 15] derived shear and cardiodial strain transformations. The co-ordinate transformation model is later extending to 3D facial data [16-17]. To derive a parametric 3D face model [18], three dimensional facial information is used [19, 20].

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In the literature various semi-automatic age progression system [5-10] are derived for aging faces of missed children. The image characteristics are well measured by texture features with respect to certain changes in direction and scales [21-25].The texture has gained lot of importance in many applications of image processing, mainly because texture extracts significant information more precisely especially the structural arrangements of a surface. The extraction of structural information of facial images place a vital role in many face recognition techniques [26- 28] , content based image retrieval [29, 30]and age group classification [31-33]. The texture information considers the behavior of a group of pixels or adjacent pixels surrounded by the current pixel instead of a single pixel. The significant facial features are also extracted from a group of pixels and the relationship between surrounding environment. In fact there is no unique meaning for texture and there is no unique definition for texture. In the literature many researchers' defined textures based on their application and the way textures are used. This research after studying the texture, its attributes and its significance defines the structure as a neighborhood property, that is the characteristics of a pixel depends upon not only the gray level value of that pixel and however the gray level values of the adjacent pixels of the neighborhood.

The texture refers the surface of an object. The texture properties can be derived locally, region wise and globally out of these three the local based methods are very popular in extracting the significant features from facial images. The local binary pattern (LBP) proposed by Ojala et al. made a significant contribution in extracting local features [34] that's why the LBP has become more popular in the literature. The LBP[34] proposed by Ojala et al. was rotational invariant. Later the LBP was converted into rotational invariant [35, 36]. The LBP based methods also used for extracting features from facial images [37, 38]. The background modeling and defection also used LBP [39]. The LBP is also used for the localization of shapes of facial images [40]. The local derivative patterns (LDP) are derived based on LBP and used for face recognition [41]. The LDP treated LBP as a non-directional first order local pattern. The LDP derived direction patterns.

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 features can be extracted more efficiently and meaningfully by using local binary pattern (LBP), textons and Motifs. The local features are extracted by deriving Motifs on a 2x2 grid by Jhanwar et al.[42]. Jhanwar et al. derived a co-occurrence matrix and gray level co-occurrence matrix (GLCM) features on Motif co-occurrence matrix (MCM) for efficient content based image retrieval (CBIR). The Motif or also termed as Peano scan motifs (PSM). The PSM provides a broader outline for handling larger dimensional data, which is not possible by the conventional methods [42]. The basic properties of PSM are listed below.

1. The PSM moves around the grid by visiting each pixel exactly once.
2. The Motif or PSMs visiting path is guided by the incremental pixel intensity values of the 2x2 grid.
3. The initial position of the PSM is fixed and PSM visits the remaining pixels based on the incremental intensities or ascending order of the remaining pixel intensities.
4. The PSM paths define a unique structure of the 2x2 grid.
5. The above three properties derives 6 Motifs on a 2x2 grid by fixing one of the position.

The Jhanwar et al.[42] fixed the left most corner of the 2x2 grid as the starting or initial position of the PSM. The six Motifs derived by Jhanwar et al[41] are shown in Fig.1.

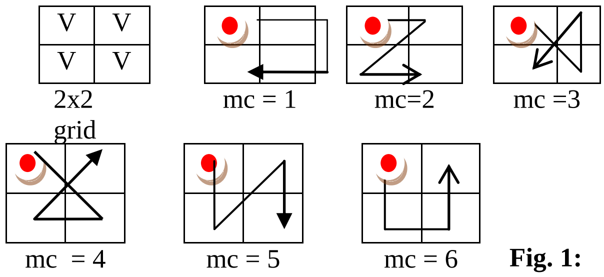

Fig. 1: A 2x2 grid and six Peano motifs.

Each of these six PSMs defines a distinctive structure and attributes and each of them derive a unique set of local information. The advantage of these six Motifs is they derive compound string by traversing the 2x2 grid based on a contrast value. Based on the outcome of the texture contrast path on a 2x2 grid a particular Motif will be resulted and this paper has given a unique code for each Motif. The index value of these Motif code ranges from 0 to 5. This paper initially divides the image into micro regions of size 2x2, and on each region the type of PSM or the path of PSM is identified by fixing the initial position of the PSM at left most corner of the grid. The 2x2 grid is assigned with PSM index ranging from 0 to 5. This process transforms the raw image into a PSM image. This paper derives a centre symmetric LBP and cross diagonal gradient code on PSM indexed image. This process transforms the facial image into a cross diagonal centre symmetric Motif pattern (CS-LBP) approach reduces the LBP code from 256 to 16 i.e. 2p to 2p/2. The centre symmetric LBP derives the binary patterns based on the relationship between symmetric sampling points of the 3x3 neighborhood.

The 3x3 neighborhood is shown below: the symmetric pixels are p0 & p4; p1 & p5; p2 &p6 and p3 & p7; each pixel value represents the derived the Motif index of a 2x2 grid.

p0	p1	p2
p7	pc	p3
p6	p5	p4

Fig. 2 : 3x3 neighborhood

This research also derives the binary relationship/ gradient relationship among cross and diagonal motifs of a 3x3 neighborhood. The cross pixels are shown in red color & diagonal pixels are shown green color in Fig.3.

p0	p1	p2
p7	pc	p3
p6	p5	p4

Fig.3: Cross and diagonal pixels of a 3x3 neighborhood.

The proposed "cross diagonal centre symmetric motif pattern (CDCSMP)" derives a code that ranges from 0 to 31 and it is given in the following equation.

$$CDCSMP = \sum_{i=0}^{3} 2^i * f(p_i, p_{i+4}) + 2^4 * f(p_1 + p_3 + p_5 + p_7, \quad p_0 + p_2 + p_4 + p_6)$$

$$where\ f(x,y) = \begin{cases} 1, & x \geq y \\ 0, & Otherwise \end{cases} \qquad (1)$$

This paper replaces the central pixel value (motif index of a micro region) with CD-CS-MM code and this process is repeated on the entire motif index image with a step length of one. This process transforms the original image into CD-CS-MM image with code values ranging from 0 to 31.

This research derives co-occurrence matrix on CD-CS-MM and derived GLCM features for varying distance d=1, 2 and 3 and for each distance value di GLCM features are computed for an angle of rotation 0o, 45o, 90o and 135o. The average GLCM features value for all four rotations is computed under each d value and this is used as feature vector for age classification.

10	26	36	51	48	52	63	94	56	32
84	59	62	35	67	84	15	96	32	51
49	56	32	18	56	91	25	48	96	52
35	48	95	63	21	54	86	52	34	62
35	63	95	34	56	32	17	89	52	16
35	85	96	41	38	96	49	64	85	21
96	52	35	48	95	62	35	48	65	18
65	19	65	48	96	35	62	48	96	32
54	85	95	74	85	63	74	84	15	36
85	62	35	62	48	56	95	63	51	84

Fig.4: 10x10 image patch.

10	26	36	51	48	52	63	94	56	32
84	59	62	35	67	84	15	96	32	51
49	56	32	18	56	91	25	48	96	52
35	48	95	63	21	54	86	52	34	62
35	63	95	34	56	32	17	89	52	16
35	85	96	41	38	96	49	64	85	21
96	52	35	48	95	62	35	48	65	18
65	19	65	48	96	35	62	48	96	32
54	85	95	74	85	63	74	84	15	36
85	62	35	62	48	56	95	63	51	84

Fig.5: Micro region based image patch

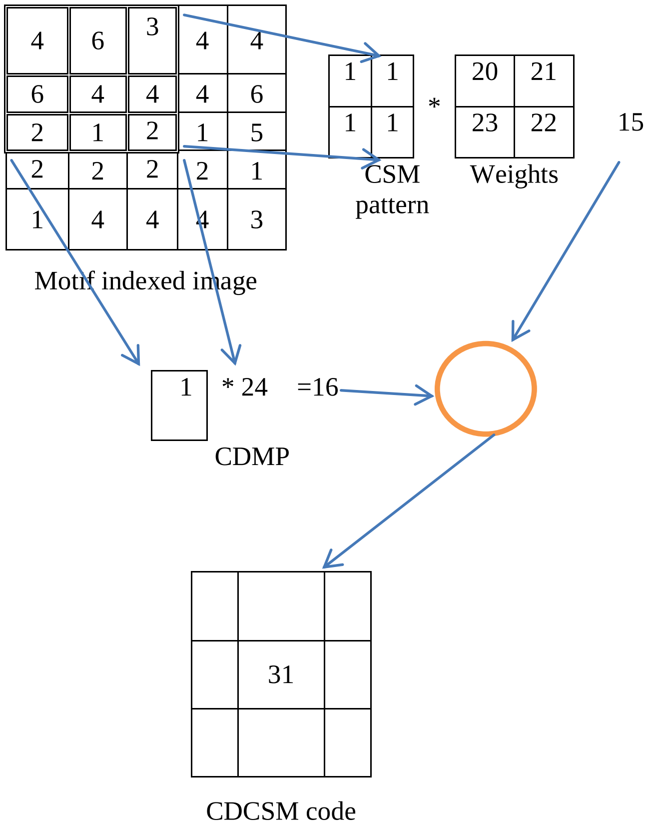

Fig. 6: CDCSM code generation process.

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 [43], 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. 7 to 9.

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Fig. 7: Sample Images of FGNET Aging Database.

Fig. 8: Sample Images of Google Database..

Fig.9 : Sample Images of Scanned Photographs.

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

Table 1: Classification rate (%) of proposed CD-CS-MM method using machine classifiers.

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

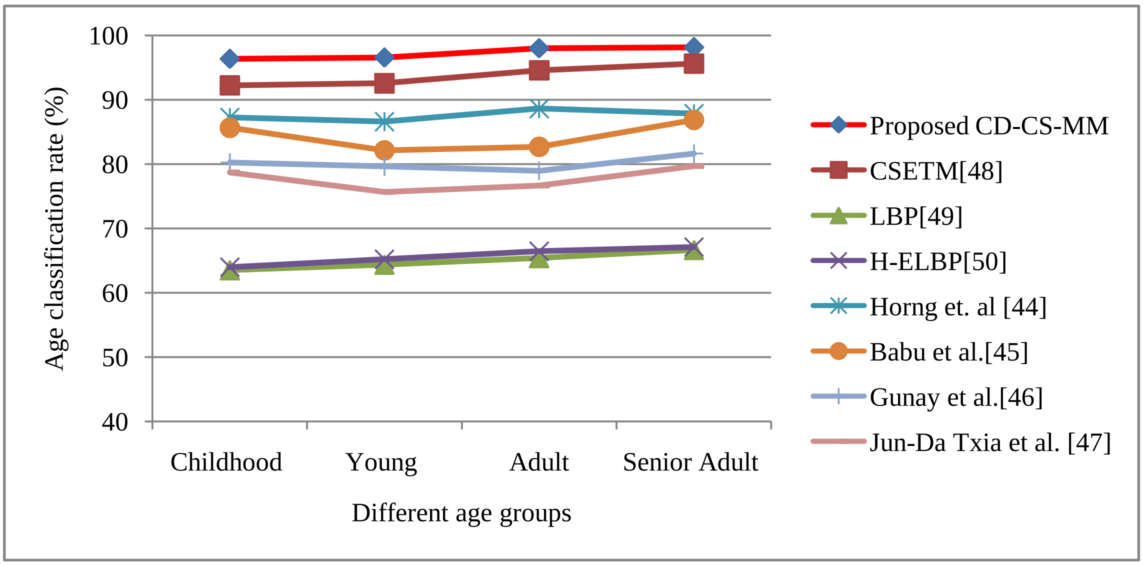

Fig. 10: Age group classification on FGNET database with four categories of age groups.

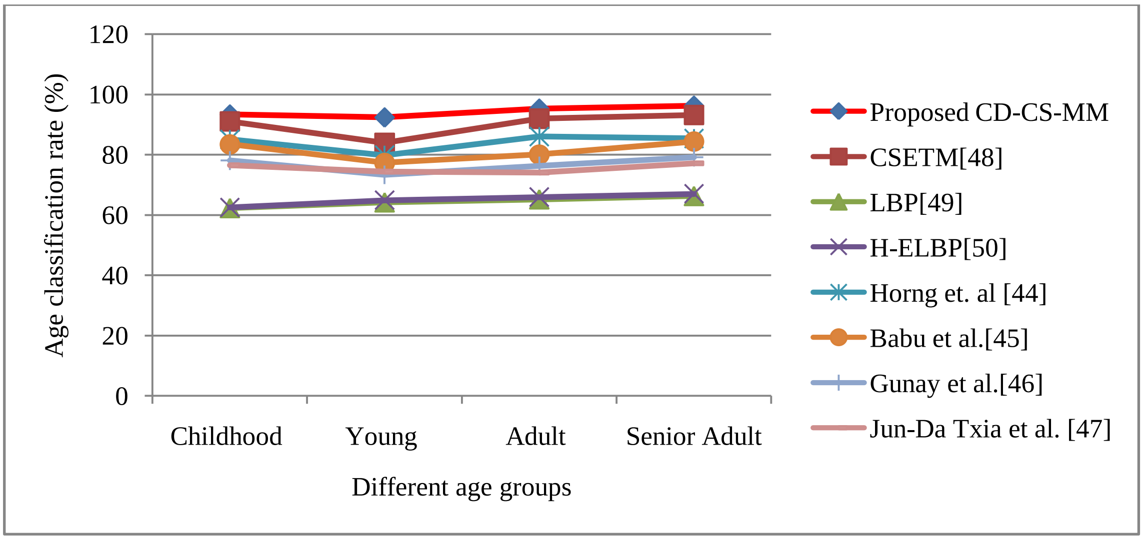

Fig. 11: Age group classification on Google database with four categories of age groups.

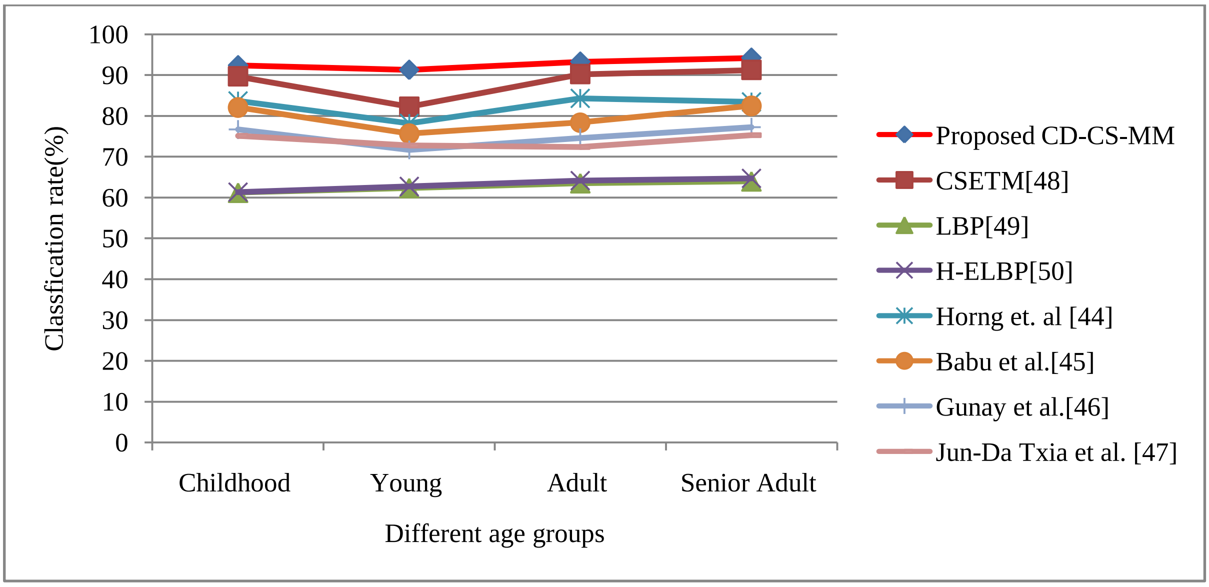

Fig. 12: Age group classification on scanned database with four categories of age groups.

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 HTDU and VTDU that preserves the significant facial features.
- Derivation of CD-CS-MM descriptor with low dimensionality based on the relative frequencies of HTDU and VTDU.
- Derivation of GLCM features on CD-CS-MM 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 CD-CS-MM 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 CDCSMP 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.
4. 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.13 to Fig.15 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.

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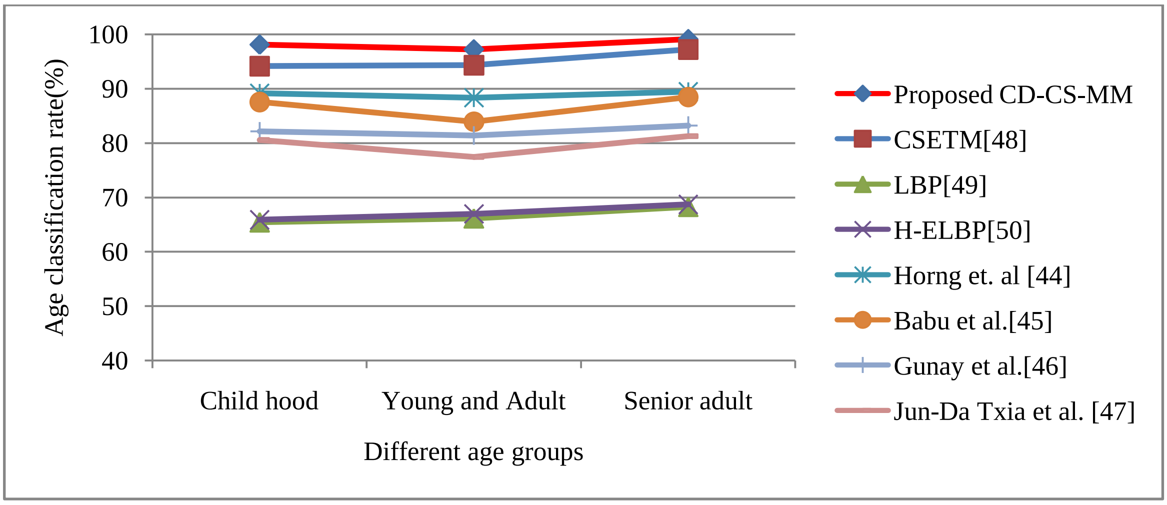

Fig.13: Comparison of proposed and existing method in terms of age group classification rate on FG-NET database with three categories.

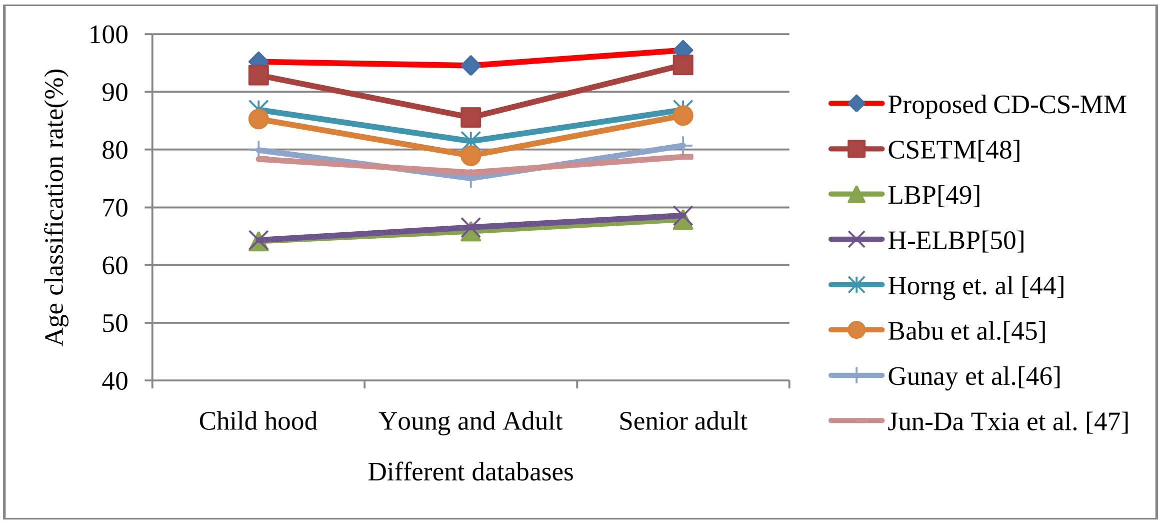

Fig. 14: Comparison of proposed and existing method in terms of age group classification rate on Google database with three categories.

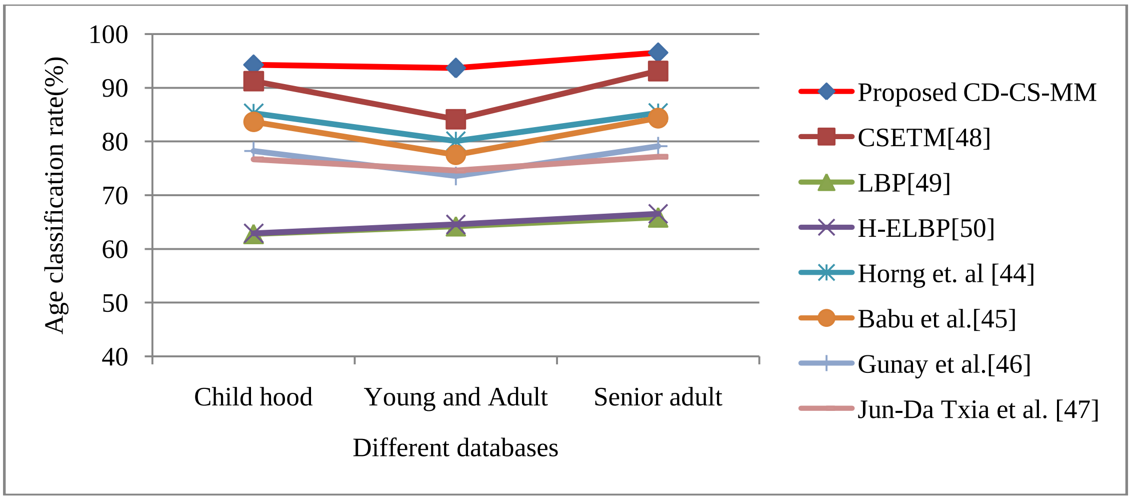

Fig. 15: Comparison of proposed and existing method in terms of age group classification rate on scanned database with three categories.

Major contribution of paper:

1. Derivation of PSM indexes on the 2x2 grid.
2. Derivation of micro features and extraction of macro features on the micro regions.
3. Derivation of centre symmetric relationship among the PSM codes.
4. Combining the cross diagonal differences with CS-relation of PSM and derivation of a unique code from this.
5. The integration of statistical features with the features derived on micro-macro regions.
6. The derivation of a CS-CD-MM with low dimensionality and with precise and significant facial features.

IV. CONCLUSIONS

This paper derived two interesting features which are contradictions to earlier macro –micro features. In the earlier methods the image is sub divided into macro regions and macro regions are sub dived in to micro regions of smaller size. The features are extracted in the micro regions. This paper derived a new direction by initially dividing the facial image into micro regions of size 2x2 and each micro region is replaced with a unique code based Peano scan motif direction. The advantage of PSM is, it provides a broader outline for handling larger dimensions. This paper divided the micro region code of PSM in to macro region of size 3 x 3. This paper then derived a centre symmetric and cross diagonal relation between motifs of a 3x3 neighborhood and the extracted code replaces the 3x3 grid. Thus the each 3x3 grid of PSM's will be replaced by a CD-CS-MM code. The GLCM features derived on CD-CS-MM represents the motif features, centre symmetric relationship between sampling points of the motif indexes, cross diagonal differences and the statistical estimation of the above. The proposed CD-CS-MM attained a high age classification rate when compared to other existing methods.

REFERENCES

1. R.Chellapa, C.L. Wilson and S.Sirohey, "Human and machine REcogniton of faces: ASurvey ,"Proc.IEEE,vil.83, no. 5, 1995.
2. IEEE Trans. Pattern Analysis and Machine Intelligence , special issue of Face and Gesture recognition, vol.19no.7, july 1997.
3. Proc. First , second , Third and Fourth Int.lConf.Face Gesture Recognition, 1995, 1996, 1998, 2000.
4. Proc. First and second Int'l Conf. Audio and video based Biometirc Person authentication, 1997, 1999
5. http:/www.rimlibrary.com/forensics/art/6.html,2001
6. http:/www.dlynnwaldron.com/ageprgression.html,2001
7. http:/www.faceslab.lsu.edu/law/ageprogression,2001
8. http:/www.missingkids.com/html/html/ageprogresiion.html, 2001
9. http:/www.outmissingchildren.ca/en/about/age.html,2001
10. M.Zimmerman, "PCs Help U.S Agency Find Missing Children, System Allows Artists to 'Age' Photos', PC Week, vil. 9 pp: 19-21, 1992
11. G.J. Edwards, C.J.Taylor, and T.F. Cootes, "Statistical Face models improving Specificity," Image and vision computing, vol.16, no.3, pp: 203-211, 1998
12. A Lantis, C.J. Taylor, and T.F. Cootes ,"Cootes, "Automatic Identification and coding of Human faces using Flexible Models,", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp: 743-756, July, 1997
13. D.W. Thompson, on Growth and Form, Cambridge Univ. Press. 1961.
14. J.B. Pittenger and R.E. Shaw, "Aging faces as Viscal-Elastic Events: Implications for a Theory of No rigid shape perceptron ,", J. Experimental Psychology: Human perceptorn and Performance, vol. 1, no.4, pp: 374-382, 1975.
15. J.B. Pittenger, R.E. Shaw, and L.S. Mark, "Perceptual Information for the age Level of Faces as a higher Order Invariant of Growth ,"J. Experimental Psychology :Human Perceptron and Performance :, vol.5, no.3 , pp: 478-493, 1979.
16. L.S. Mark and J.T. Todd, "The Perceptorn of Growth in Three Dimensions, "Perceptron and Psychophysics, vol. 33, no. 2, pp: 193-196, 1983.
17. V. Bruce, M. Burton, T. Doyle, and N.Dench, "Further Experiments on the Perceptron of Growth in three Dimensions", Perceptron and Psychophysics, vol. 46, no.6, pp: 528-536, 1989.
18. V. Blanz and T. Vetter, " AMorphable Model for the Synthesis of 3D Faces,", Computer Graphics Proceedings –Ann. Conf. Series, pp: 187-194, 1999.
19. A.J. O Toole, T. Vetter, H.Volz, and E.Salter, "Three- Dimensional Caricatures of Human Heads : Distinctiveness and the Perceptorn of Age:, PErceptorn, vol. 26, pp: 719-732, 1997.
20. A.J. Toole, T. Price, T. Vetter, J.C, Bartlett, and V. Blanz, "3D Average in Attractivenncess and Ge", Imge and Vision Computing , vol. 18, no. 1, pp: 9-20, 1999.
21. D. Gabor. Theory of communication. Journal IEEE, 93:429–459, 1946.
22. H. Jeong and I. Kim. Adaptive determination of filter scales for edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(5):579–585, May 1992
23. T. Lindeberg. Scale-Space Theory in Computer Vision. Kluwer, Boston, 1994.
24. T. Lindeberg. Principles for automatic scale selection. In B. Jahne, H. Haußecker, and ¨ P. Geißler, editors, Handbook on Computer Vision and Applications, volume 2, pages 239– 274. Academic Press, Boston, USA, 1999.
25. S. Marcelja. Mathematical description of the response of simple cortical cells. Journal of Optical Society of America, 70:1297–1300, 1980.
26. A. Mallikarjuna Reddy, V. Venkata Krishna, L. Sumalatha, "Face recognition based on stable uniform patterns" International Journal of Engineering & Technology", Vol.7 ,No.(2),pp.626-634, 2018
27. A. Mallikarjuna Reddy, V. Venkata Krishna, L. Sumalatha, "Efficient Face Recognition by Compact Symmetric Elliptical Texture Matrix (CSETM)", Jour of Adv Research in Dynamical & Control Systems, Vol. 10, 4-Regular Issue, 2018.
28. A. M. Reddy, V. V. Krishna, L. Sumalatha and S. K. Niranjan, "Facial recognition based on straight angle fuzzy texture unit matrix," 2017 International Conference on Big Data Analytics and Computational Intelligence (ICBDAC), Chirala, 2017, pp. 366-372.
29. A.Obulesu, V. Vijay Kumar, L. Sumalatha , "Image Retrieval based Local Motif Patterns Code ", I.J. Image, Graphics and Signal Processing, 2018, 6, 68-78.
30. A.Obulesu,V. Vijay Kumar,L. Sumalatha, "Cross Diagonal Derivation Direction Matrix for Efficient Image Retrieval", Jour of Adv Research in Dynamical & Control Systems, Vol. 10, No. 4, pg.284-295, 2018
31. V.Vijaya Kumar, P.J.S. Kumar , Pullela S V V S R Kumar, "Age classification of facial images using third order neighbourhood Local Binary Pattern" , International Journal of Applied Engineering Research (IJAER), Vol. 10, Iss.15, 2015, pp: 35704-35713, ISSN 0973-4562.
32. Pullela R Kumar, V. Vijaya Kumar, Rampay.Venkatarao, "Age classification based on integrated approach". International Journal Of Image, Graphics And Signal Processing (IJIGSP), Vol. 6, Iss.7, 2014, pp. 50-57, ISSN: 2074-9082.
33. V. VijayaKumar ,Jangala. SasiKiran , V.V. HariChandana, " An effective age classification using topological features based on compressed and reduced grey level model of the facial skin", International journal of image, graphics and signal processing (IJIGSP), , Vol.6, Iss.1, 2013, pp.9-17, ISSN: 2074-9082.
34. T. Ojala, M. Pietikainen, and D. Harwood, "A Comparative Study of Texture Measures with Classification Based on Feature Distributions", Pattern Recognition, vol. 29, pp. 51-59, 1996.
35. T. Ojala, M. Pietikainen, T. Maenpaa, Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns, IEEE Trans. PAMI 24 (7) (2002) 971–987
36. Z. Guo, Q. Li, L. Zhang, J. You, D. Zhang, W. Liu, Is Local Dominant Orientation Necessary for the Classification of Rotation Invariant Texture?, Neurocomputing 116 (2013) 182–191.

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37. X. Qi, R. Xiao, C. Li, Y. Qiao, J. Guo, X. Tang, Pairwise Rotation Invariant Co-Occurrence Local Binary Pattern, IEEE Trans. PAMI 36 (11) (2014) 2199–2213.
38. X. Sun, J. Wang, M. F. She, L. Kong, Scale Invariant Texture Classification via Sparse Representation, Neurocomputing 122 (2013) 338–348.
39. L. Sifre, S. Mallat, Rotation, Scaling and Deformation Invariant Scattering for Texture Discrimination, in: CVPR, 2013, pp. 1233–1240
40. Y. Zhao, D.-S. Huang, W. Jia, Completed local binary count for rotation invariant texture classification, IEEE Trans. Image Processing 21 (10) (2012) 4492–4497.
41. T. Jabid, M. H. Kabir, and O. Chae, “Local directional pattern (LDP)–A
42. T. Jabid, M. H. Kabir, and O. Chae, “Local directional pattern (LDP)–A robust image descriptor for object recognition,” In Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on (pp. 482-487).
43. Jhanwar N, Chaudhuri S, Seetharaman G, Zavidovique B. Content-based image retrieval using motif co-occurrence matrix. Image Vision Computing 2004;22:1211–20.
44. FG-NET (Face and Gesture Recognition Network): http://wwwprima.inrialpes.fr/FGnet/ (2014), [Online; accessed 10-June-2014]
45. W. B. Horng, C. P. Lee, and C. W. Chen, “Classification of age groups based on facial features,” Tamkang J. Sci. Eng. 4(3), 183–192 (2001).
46. C. R. Babu, E. S. Reddy, and B. P. Rao, “Age group classification of facial images using rank based edge texture unit (RETU),” ProcediaComput. Sci. 45, 215–225 (2015).
47. A. Gunay, V.V. Nabiyev, Automatic age classification with LBP, in: 23rd International Symposium on Computer and Information Sciences, ISCIS 008 (2008) 1–4.
48. Jun-Da Txia, Chung-Lin Huang, Age estimation using AAM and local facialfeatures, in: International conference on Intelligent Information Hiding and Multimedia Signal Processing (2009) 885–888
49. A. Mallikarjuna Reddy, V. Venkata Krishna, L. Sumalatha, Efficient Face Recognition by Compact Symmetric Elliptical Texture Matrix (CSETM), Jour of Adv Research in Dynamical & Control Systems, Vol. 10, 4-Regular Issue, 2018.
50. T. Ojala, M. Pietikainen and T. Maenpaa, “Multi-resolution gray- scale and rotation invariant texture classification with local binary patterns,” PAMI, 24 (7), 971–987, 2002
51. K. Subba Reddy , V. Vijaya Kumar, A.P. Siva Kumar, Classification of Textures Using a New Descriptor Circular and Elliptical-LBP (CE-ELBP), International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 19 (2017) pp. 8844-8853.

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