Gender Classification using Central Fibonacci Weighted Neighborhood Pattern Flooding Binary Matrix (CFWNP_FBM) Shape Primitive Features

P.Chandra Sekhar Reddy, G R Sakthidharan, S. Kanimozhi Suguna, J. Mannar Mannan, P Varaprasada Rao

Abstract*: Gender Classification from facial images is an open research area with wide range of computer vision applications like security, biometrics and human computer interaction applications. In the proposed method the LL band image of facial image is obtained by using wavelet then on this image Fibonacci Weighted Neighborhood Central pixel Flood binary Matrix is computed and then shape features are evaluated. SVM method uses these shape features for gender classification. The proposed approach has been experimented on FG NET database. The experimental results has shown the more accuracy compared to with other existing methods.

***Keywords* : Gender Classification, biometrics, Fibonacci Weighted Neighborhood Central pixel Flood binary, FG NET**

I. INTRODUCTION

Humans can easily identify gender of the persons by looking at face or facial images. The aim of automatic gender classification is to find the features from facial images. The progress of gender classification research has driven in many potential applications like access control systems in smart spaces, human-computer interaction (HCI), the security and surveillance industry, demographic research, commercial development, and mobile application and video games. Research on gender classification using facial images started at the in 1990s. Many researchers proposed various methods for Gender Classification with features like face, eyebrow, fingernail, gait, motion, gesture, fingerprint, iris, voice, emotion-speech, ear, etc. and bio-signals features (ECG, EEG, DNA, etc.). However, it is still a challenging task to definitely automate gender classification. In this paper, proposed method uses local information based shape primitives as features for gender recognition. This paper is organized into sections as: Section I gives introduction, Section II is an overview of related work. Proposed model is described in Section III. Experimental results and discussion are given in Section IV. Conclusion are presented in Section V.

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II. RELATED WORK

Researchers have explored gender classification using face [1, 2, 3]. Chen and Ross [1] used utilized near-infrared and thermal face images for gender recognition using SVM, Adaboost and LDA classifiers. Danisman et. al. proposed fuzzy inference system (FIS) with inner and outer facial features [2]. The authors used different classifiers with LBP as features. Gender recognition by combining the registered range from facial scans and intensity images [3]. Researchers have also investigated ear [4], fingerprint [5], hand geometry [6] and iris biometrics [7] for gender identification. Due to its simplicity and effectiveness, LBP [8], FWNP [9] and Central Local Binary Pattern based Structure Co-occurrence Features [10] are used in face recognition and age classification. Lian and Lu [11] utilizes LBP based textural features from face sub regions. Researchers also attempted with fusion of multiple biometric traits for gender classification. Li et al. [5] have employed fusion of fingerprint and face for gender recognition. Authors in Shan et al. [12] and Zhang and Wang [13] have performed gender classification using face and gait.

III. METHODOLOGY

The proposed method is shown in the block diagram of Fig.1 and explained in detail in the following sub sections.

Step 1. Image Preprocessing

The original colour image is converted into a grey level image and then face part detected from grey level images, shown in figure1.

Step 2: Fibonacci Weighted Neighborhood Pattern

The local neighborhood information of pixels are represented with FWNP values. It is same as computing Local Binary Pattern(LBP) with Fibonacci weights {1,1,2,3,5,8,13,21} instead of binary weights {1,2,4,8,16,32,64,128} and this FWNP [9] and LBP computing are shown in figure 3.

FWNP for each pixel in the image with their neighborhoods is represented by pattern with range of integers from 0 to 54, whereas Local Binary pattern (LBP) ranging 0 to 255. In FWNP only first 20 percent of Local Binary patterns are used for representing neighborhoods relation.

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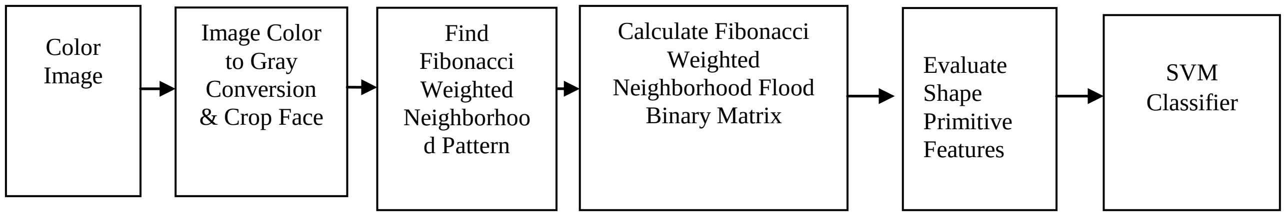

Fig.1: CFWNP_FBM Shape Primitive Features for Gender Classification

Fig.2: Grey Conversion and Face Detection

$$\begin{array}{|c|c|c|}\hline p_1 & p_2 & p_3 \\ \hline p_8 & p_c & p_4 \\ \hline p_7 & p_6 & p_5 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline b_1 & b_2 & b_3 \\ \hline b_8 & & b_4 \\ \hline b_7 & b_6 & b_5 \\ \hline \end{array} \; X \; \begin{array}{|c|c|c|}\hline 1 & 1 & 2 \\ \hline 21 & & 3 \\ \hline 13 & 8 & 5 \\ \hline \end{array} \rightarrow \text{LBP}$$

$$\begin{array}{|c|c|c|}\hline 45 & 80 & 110 \\ \hline 120 & 96 & 78 \\ \hline 120 & 95 & 65 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline 0 & 0 & 1 \\ \hline 1 & & 0 \\ \hline 1 & 0 & 0 \\ \hline \end{array} \; X \; \begin{array}{|c|c|c|}\hline 1 & 2 & 4 \\ \hline 128 & & 8 \\ \hline 64 & 32 & 16 \\ \hline \end{array} \rightarrow 196$$

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$$\begin{array}{|c|c|c|}\hline 45 & 80 & 110 \\ \hline 120 & 96 & 78 \\ \hline 120 & 95 & 65 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline 0 & 0 & 1 \\ \hline 1 & & 0 \\ \hline 1 & 0 & 0 \\ \hline \end{array} \; X \; \begin{array}{|c|c|c|}\hline 1 & 1 & 2 \\ \hline 21 & & 3 \\ \hline 13 & 8 & 5 \\ \hline \end{array} \rightarrow 36$$

Fig. 3: Computation of LBP and FWNP.

Step 3. Central FWNP Flooding Binary Matrix (CFWNP_FBM)

The central FWNP flooding binary structure forms a group of FWNP values which have the same value as the central FWNP value over the 3x3 neighborhood. In a 3x3 FWNP, the neighbors with same central FWNP are set to 1 otherwise, it is set to zero. This formed 3x3 binary pattern is central FWNP flooding binary structure.

Computing the CFWNP_FBM over FWNP Image is described as follows.

(1) Central FWNP flooding binary structures CFBS1(p,q), CFBS2(p,q), CFBS3(p,q) and CFBS4(p,q) are computed starting from positions (1,1), (1,2), (2,1) and (2,2) respectively with 3x3 block size from left-to-right and top-to-bottom throughout FWNP image CFBS(m,n) with a step-length of three in both horizontal and vertical directions.

(2) Central FWNP flooding binary matrix, denoted by CFWNP_FBM (p,q) is computed using equation 1.

$$CFWNP\_FBM(p,q) = (CFBS1(p,q) \vee CFBS2(p,q) \vee CFBS3(p,q) \vee CFBS4(p,q)) \quad (1)$$

i.e. ∨ - is OR operation of CFBS1(p,q), CFBS2(p,q), CFBS3(p,q) and CFBS4(p,q) values at position (p,q).Central FWNP Flooding Binary Matrix detection is shown in Fig.4.

Step 4. Evaluation of Shape Primitives

The shape primitives on 3x3 block are defined as follows. In Line Intersect Shape Primitive (LISP), nonzero binary elements occur in middle row and middle column and other elements are zeros.

Diagonal Intersect Shape Primitive (DISP) contains non zero binary elements on principal diagonals. In Horizontal Mid Line Shape Primitive (HMLSP) and Vertical Mid Line Shape Primitive (VMLSP) non zeros occur only in horizontal middle line and vertical middle line respectively. Intersect Line Diagonal Shape Primitive (ILDSP) contains all elements as nonzero. Centre Pixel Shape Primitive (CPSP) is only nonzero at central position. These primitives are shown in Fig.5. The number of occurrences of these shape primitives features are evaluated on Central FWNP Flooding Binary Matrix.

8	7	8
8	8	4
5	8	9

(a) 3x3 block with gray values

1	0	1
1	1	0
0	1	0

(b) Central pixel flood binary structure

5	5	7	9	2	3	8
4	6	9	1	8	8	8
3	3	6	1	3	4	4
8	5	5	3	1	6	4
5	8	9	5	1	4	4
4	8	9	9	5	4	6
8	9	5	3	5	4	4

(c) Sub FWNP image

0	0	0	0	0	0	0
0	1	0	0	1	1	0
0	0	1	0	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0

(d) CFBS1(p,q)

0	0	0	1	0	0	1
0	0	1	0	1	1	1
0	0	0	0	0	0	0
0	0	0	0	1	0	1
0	0	1	0	1	1	1
0	0	1	1	0	1	0
0	0	0	0	0	0	0

(e) CFBS2(p,q)

0	0	0	0	0	0	0
0	0	0	0	0	0	0
1	1	0	0	1	0	0
0	0	0	1	0	0	0
0	1	0	1	0	0	0
0	1	0	0	1	0	0
1	0	0	0	1	0	0

(f) CFBS3(p,q)

0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	1	0	0	1	1
0	0	0	0	0	0	1
0	0	1	0	0	1	1
0	0	1	1	0	1	0
0	0	0	0	0	1	1

(g) CFBS4(p,q)

0	0	0	1	0	0	1
0	1	1	0	1	1	0
1	1	1	0	0	1	1
1	0	0	1	1	0	1
0	1	1	1	1	1	1
0	1	1	1	1	1	0
1	0	0	0	1	1	1

(h) central pixel flooding binary matrix

Fig.4. Computing Central pixel flooding binary matrix

0	1	0
1	1	1
0	1	0

(a) LISP

1	0	1
0	1	0
1	0	1

(b) DISP

0	0	0
1	1	1
0	0	0

(c) HMLSP

0	1	0
0	1	0
0	1	0

(d) VMLSP

1	1	1
1	1	1
1	1	1

(e) ILDSP

0	0	0
0	1	0
0	0	0

(f) CPSP

Fig.5. Shape Primitives

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

To figure out the gender classification performance of the proposed method, experiments are carried over FG-NET database of facial images and sample of these images are shown in figure 6. The frequency occurrences of LISP, DISP, HMLSP, VMLSP, ILDSP and CPSP are evaluated on Central FWNP Flooding Binary Matrix of considered database images. These evaluated features are represented in table1. From the experimental study, it is observed that features HMLSP, VMLSP, ILDSP and CPSP are considered as significant features in gender recognition. These considered features with SVM Classification algorithm has given 96% correct classification rate in gender recognition. Proposed method with shape primitive features outperforms with more accuracy compared to other existing methods. Comparison of proposed method with other methods for gender classification is shown in table 2 and figure 7.

V. CONCLUSION

In this paper, we proposed approach for gender recognition based on shape primitives' features extraction on CFWNP_FBM. FWNP is a new method for identifying local information, the orientation of FWNP as a structure with binary shape primitives. Experiment carried out with this method on considered data set given gender recognition accuracy of 96%. A comparison of our proposed scheme with the other methods indicates a better performance in terms of accuracy. Future work can be directed CFWNP_FBM with new shape patterns, soft biometric traits and textural properties as features for gender classification.

Fig.6. FG-NET database sample images

Table 1. The frequency of occurrences of LISP, DISP, HMLSP, VMLSP, ILDSP and CPSP shape primitives

S.no	Image	LISP	DISP	HMLSP	VMLSP	ILDSP	CPSP
1	001A18	0	0	57	59	51	3213
2	001A19	0	0	107	31	23	3185
3	001A22	1	0	125	59	116	3277
4	001A29	0	0	78	86	24	3329
5	001A33	1	0	58	90	40	4590
6	003A20	0	0	11	3	6	3563
7	003A49	0	0	90	100	73	3017
8	003A60	0	0	35	60	24	3446
9	003A61	0	0	54	77	72	3021
10	004A19	0	0	72	2	1	4522
11	004A21	0	0	56	43	27	3062
12	006A36	0	0	44	20	26	3759
13	006A42	1	0	55	64	72	3306
14	006A46	1	0	27	26	24	3956
15	006A51	1	0	65	87	80	3022
16	006A67	0	0	82	76	65	3026
17	012A14	0	0	57	40	175	2556
18	012A23	1	0	51	53	27	2690
19	012A24	1	0	59	38	95	2726
20	012A26	1	0	104	76	62	2675
21	012A27	1	1	68	102	93	2835
22	026A13	0	1	38	48	112	2531
23	026A15	1	1	54	44	91	2886
24	026A17	1	0	49	43	123	2901
25	026A18	1	0	28	47	49	2376
26	026A19	0	0	34	43	26	2665
27	054A09	1	0	76	57	182	2075
28	054A10	0	0	65	54	72	2722

Table2. Comparison of Gender classification methods with facial Features

	Feature Extraction Algorithms	Database	Accuracy
Face Images	Shape primitives on CFWNP_FBM	FG NET	96%
	Adaboost-LBP[14]	LFW	94.81%
	LBP [15]	BCMI and FERET	90%

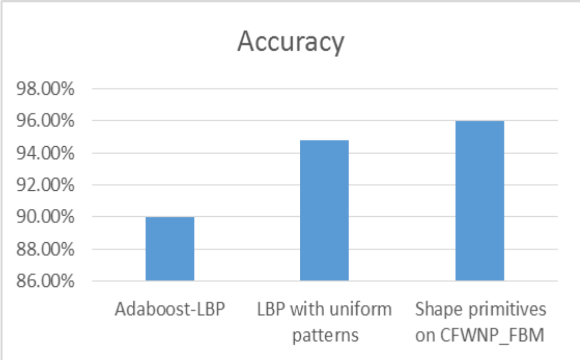

Fig.7. Proposed method accuracy rate with other methods

REFERENCES

1. Chen, C., & Ross, A., Evaluation of gender classification methods on thermal and near-infrared face images. In International joint conference on biometrics (IJCB) (pp. 1–8), 2011.
2. Danisman, T., Bilasco, I. M., & Martinet, J. , Boosting gender recognition performance with a fuzzy inference system. Expert Systems with Applications, 42(5), 2772–2784, 2015.
3. Lu, X., Chen, H., & Jain, A. K., Multimodal facial gender and ethnicity identification. Proceedings of Advances in Biometrics, 3832, 554–561. 2005.
4. Gnanasivam, P., & Muttan, S., Gender classification using ear biometrics. In Proceedings of the 4th International Conference on Signal and Image Processing (ICSIP) (pp. 137–148). 2012.
5. Li, X., Zhao, X., Fu, Y., & Liu, Y. , Bimodal gender recognition from face and fingerprint. In IEEE conference on computer vision and pattern recognition (CVPR) (pp. 2590–2597). 2010
6. Wu, M., & Yuan, Y. Gender classification based on geometry features of palm image. Hindawi Publishing Corporation, The Scientific World Journal, 2014, 1–7. 2014.
7. Thomas, V., Chawla, N. V., Bowyer, K. W., & Flynn, P. J., Learning to predict gender from iris images. IEEE international conference on biometrics: Theory, applications, and systems. 2007.
8. T. Ojala, M. Pietikäinen, D. Harwood, A comparative study of texture measures with classification based on Featured distributions, Pattern Recogn. 29 (1) ,51–59, 1996.
9. Chandra Sekhar Reddy P., Vara Prasad Rao P., Kiran Kumar Reddy P., Sridhar M. (2019) Motif Shape Primitives on Fibonacci Weighted Neighborhood Pattern for Age Classification. In: Wang J., Reddy G., Prasad V., Reddy V. (eds) Soft Computing and Signal Processing. Advances in Intelligent Systems and Computing, vol 900. Springer, Singapore.
10. P Chandra Sekhar Reddy et. al. "Age Grouping with Central Local Binary Pattern based Structure Co-occurrence Features", in International conference on Smart Systems and Inventive Technology(ICSSIT 2018), Tirunalveli, Dec. 2018, pp. 107-112.
11. Hui-Cheng Lian and Bao-Liang Lu. Multi-view gender classification using local binary patterns and support vector machines. Advances in Neural Networks, volume 3972, pages 202–209. Springer Berlin Heidelberg, 2006.
12. Shan, C., Gong, S., & Mc Owan, P. W. Fusing gait and face cues for human gender recognition. Neuro computing, 71 (10-12), 1931–1938. 2008.
13. Zhang, D., & Wang, Y. Gender recognition based on fusion of face and multi-view gait. Advances in Biometrics Lecture Notes in Computer Science, 5558, 1010–1018. 2009.
14. Caifeng Shan. Learning local binary patterns for gender classification on real-world face images. Pattern Recognition Letters, 33:431–437, 2013.
15. Bing Li, Xiao-Chen Lian, and Bao-Liang Lu. Gender classification by combining clothing, hair and facial component classifiers. Neurocomputing, 76(1):18–27, 2012.

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