Age Classification for work sustainability using SVM using Co-occurrence features on Fibonacci Weighted Neighborhood Pattern Matrix

P.Chandra Sekhar Reddy[1]*, *K.S.R.K.Sarma*[2], *T. Raghunadha Reddy*[3], *Sarangam Kodati*[4], *Rajeev Kumar*[5], *M. Dhasaratham*[6]

[1]CSE Department, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Telangana, India
[2]CSE Department, Vidya Jyothi Institute of Technology, Hyderabad, Telangana, India
[3]CSE Department, Matrusri Engineering College, Hyderabad, Telangana, India
[4]CSE Department, CVR College of Engineering, Hyderabad, Telangana, India
[5]Uttaranchal Institute of Management, Uttaranchal University, Dehradun, India
[6]Department of Information Technology, TKR College of Engineering and Technology, Hyderabad, Telangana, India

Abstract: Computer vision systems are increasingly focusing on age recognition from facial images. To solve this problem, In this paper, proposed a method that computes the Fibonacci Weighted Neighborhood Pattern on an image to obtain local neighborhood information, then evaluates Co-occurrence features for work sustainability age classification with SVM classifier. These characteristics show how people's ages differ. The proposed method has been tested on the FG-Net facial images dataset as well as other scanned images. Experiments showed that the proposed approach outperformed other currently existing methods.

1. Introduction

Age classification plays a key role in classifying facial images. In the past two decades, age classification of people from facial photographs has gained prominence due to applications such as human-computer interaction, electronic customer relationship management, video surveillance tracking, and others. Age classification techniques can be divided into three categories. Anthropometric models, aging pattern subspaces, and age regression categories make up this trio. A wrinkling analysis of the face and the Cranio-facial development model are both included in the anthropometric model. The Active Appearance Model (AAM), a technique for age regression, is used to extract facial elements linked to shape and appearance. The estimation of age using the texture feature [1, 2], the contour and texture features [3, 4] Recent research has focused on LBP models, which represent spectral patterns in ECG data. Various age classification and grouping systems have recently been developed with LBP models, spectral patterns in ECG data, and by Sakthidharan et.al.[5], Reddy et al. [6,7] and other researchers [8,9,10]. Research has shown that individuals of different ages hold different work attitudes[11]. The current paper considers two age categories for age classification, child, and adult, in order to discuss this study in age grouping. The present paper evaluates Co-occurrence features on FWNPM of facial images and uses SVM Classifier. The rest of the manuscript is organized as follows: section 2 describes the methodology, the results are discussed in Section 3 and conclusions are made in section 4.

2. Methodology

The proposed method converts a colour image to a grey image, computes the Fibonacci Weighted Neighborhood Pattern (FWNPM), and then evaluates co-occurrence features for age classification as shown in figure 1.

* Corresponding author: pchandureddy@yahoo.com

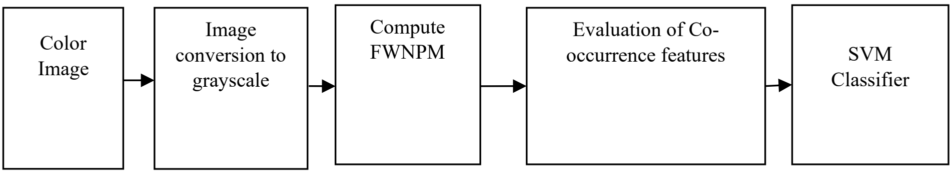

Fig.1. Age Classification

Step -1: Image conversion from colour to gray scale

The colour image is converted to the grayscale image by removing the hue and saturation characteristics while preserving the brightness information.

Step-2: Fibonacci Weighted Neighborhood Pattern Matrix

LBP is a two-dimensional approach to representing surface textures that includes two complementary measures: local spatial patterns and grayscale contrast. By thresholding the 3 x 3 neighborhood of each pixel with the mean and looking at the output as a binary integer, the original LBP generates labels from 0 to 255 for image pixels.

The FWNPM is used to extract local neighborhood information from pixels in an image[6]. In Our approach, each pixel in the image produces FWNPM, which can be used to represent local pixel information using an integer code spanning from 0 to 54, reducing the number of permissible encoding options by 20%. An example of how to compute this pattern is shown in Figure 2. P = p_c, p_1,..., p_8, where p_c is the central pixel intensity value and p_l (1<=l<=8) is intensities of surrounding pixels, makes up a 3x3 neighborhood. A set of binary values d_l (1<=l<=8) can then be used to describe each of the image's 3x3 neighborhoods, as shown in equation 1. .

$$d_l = \begin{cases} 1 & p_l - p_c \geq 0 \\ 0 & p_l - p_c < 0 \end{cases} \qquad (1)$$

The equation 2 is used to calculate FWNPM for each of the 3x3 neighborhoods.

$$\mathrm{FWNPM} = \sum_{k=1}^{8} d_k \times w_k \qquad (2)$$

where $w_{1,2,3..8} = \{1,1,2,3,5,8,13,21\}$.

$$\begin{bmatrix} p_1 & p_2 & p_3 \\ p_8 & p_c & p_4 \\ p_7 & p_6 & p_5 \end{bmatrix} \rightarrow \begin{bmatrix} b_1 & b_2 & b_3 \\ b_8 & & b_4 \\ b_7 & b_6 & b_5 \end{bmatrix} \times \begin{bmatrix} 1 & 1 & 2 \\ 21 & & 3 \\ 13 & 8 & 5 \end{bmatrix} \rightarrow \mathrm{FWNPM}$$

$$\begin{bmatrix} 45 & 50 & 9 \\ 25 & 40 & 36 \\ 60 & 26 & 43 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & 0 \\ 0 & & 0 \\ 1 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 1 & 1 & 2 \\ 21 & & 3 \\ 13 & 8 & 5 \end{bmatrix} \rightarrow 20$$

Fig. 2. Calculation of FWNPM

Step 3: Evaluation of Co-occurrence Features on FWNPM

Haralick proposed a statistical method for texture analysis based on a gray scale spatial dependence co-occurrence matrix and extracted 14 features[12]. He applied these functions to classification tasks on three different types of datasets: aerial, photomicrograph, and satellite imagery, with accuracy ranging from 83 to 89 percent. He also explained that not all characteristics are necessary for classification. Subsequently, numerous authors experimented with a subset of the Haralick features in image processing applications.

Our method assesses the contrast, correlation, energy, and local homogeneity of the feature set on FWNPM. These features make these methods optimal for many face detection, age group, and other image processing applications. These characteristics are calculated using Equations 3 through 6 on FWNPM in four directions for successful age classification: 0, 45, 90, and 135.

$$\text{contrast} = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right) P_{ij} \qquad (3)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right)^2 \qquad (4)$$

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \qquad (5)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (6)$$

Step 4: Support Vector Machines

Support Vector Machines are supervised machine learning algorithms that can be adopted for classification and regression. They have lately gained popularity owing to their capacity to handle large numbers of continuous and categorical variables. In multidimensional space, an SVM model is a portrayal of various classes in a hyper plane. SVM builds the hyper plane iteratively to lessen the error. The objective of SVM is to partition datasets into bins to find the best boundary hyper plane (MMH).

3. Results and Discussions

The proposed method created a database of 1002 face images from the FG-NET database and 600 scanned photographs images, as shown in Fig.3. The features contrast, correlation, energy and homogeneity are extracted from the Fibonacci-weighted neighborhood pattern matrix of the database images under consideration and the results are stored in the feature vector. The training images are represented using the feature set. Tables 1, 2, 3, and 4 show the derived four characteristics on five facial images in four directions with 0° 45°, 90°, and 135° orientation of FWNPM. For age classification, these 16 features are used as feature vectors. These features, together with the SVM Classification algorithm, resulted in a 99.2% accuracy rate in age classification. Proposed method obtains state of the art results outperforming all previous methods. The results of this method are in agreement with our expectations. Table 5 and Figure 4 show a comparison of the proposed system and other age classification methods.

Fig.3. FG-NET Database image samples

Table 1. Co-occurrence Features with 0° on FWNP

S.no	Image	Contrast_ FWNPM 0°	Correlation_ FWNPM 0°	Energy_ FWNPM 0°	Homogeneity_ FWNPM 0°
1	002A05	3.749412	-0.03978	0.855745	0.933046

2	002A07	4.223876	-0.04504	0.838743	0.924574
3	004A19	4.244281	-0.04527	0.838018	0.924209
4	005A18	5.290251	-0.05706	0.801556	0.905531
5	009A13	4.028041	-0.04286	0.845727	0.928071
6	028A34	0.389778	-0.00399	0.984186	0.99304
7	028A35	2.122934	-0.02214	0.916165	0.96209
8	028A37	1.397267	-0.01446	0.944188	0.975049
9	028A41	0.427046	-0.00438	0.982683	0.992374
10	030A20	1.287903	-0.01332	0.948469	0.977002

Table 2. Co-occurrence Features with 45° on FWNP

S.no	**Image**	**Contrast_ FWNPM 45°**	**Correlation_ FWNPM 45°**	**Energy_ FWNPM 45°**	**Homogeneity_ FWNPM 45°**
1	002A05	3.748444	-0.03977	0.85578	0.933064
2	002A07	4.222012	-0.04502	0.838809	0.924607
3	004A19	4.24439	-0.04527	0.838014	0.924207
4	005A18	5.290351	-0.05706	0.801552	0.905529
5	009A13	4.023873	-0.04282	0.845876	0.928145
6	028A34	0.390679	-0.004	0.984149	0.993024
7	028A35	2.126466	-0.02218	0.91603	0.962027
8	028A37	1.398305	-0.01447	0.944148	0.97503
9	028A41	0.427793	-0.00438	0.982653	0.992361
10	030A20	1.286752	-0.0133	0.948514	0.977022

Table 3. Co-occurrence Features with 90° on FWNP

S.no	**Image**	**Contrast_ FWNPM 90°**	**Correlation_ FWNPM 90°**	**Energy_ FWNPM 90°**	**Homogeneity_ FWNPM 90°**
1	002A05	3.75487	-0.03984	0.855548	0.932949
2	002A07	4.237375	-0.04519	0.838263	0.924333
3	004A19	4.242683	-0.04525	0.838075	0.924238
4	005A18	5.294992	-0.05712	0.801394	0.905447
5	009A13	4.021717	-0.04279	0.845953	0.928184
6	028A34	0.389726	-0.00399	0.984188	0.993041
7	028A35	2.122264	-0.02214	0.916191	0.962102
8	028A37	1.396662	-0.01446	0.944212	0.97506
9	028A41	0.428498	-0.00439	0.982625	0.992348

10	030A20	1.284328	-0.01328	0.948609	0.977066

Table 4. Co-occurrence Features with 135° on FWNP

S.no	Image	Contrast_ FWNPM 135°	Correlation_ FWNPM 135°	Energy_ FWNPM 135°	Homogeneity_ FWNPM 135°
1	002A05	3.748444	-0.03977	0.85578	0.9330635
2	002A07	4.222257	-0.04502	0.8388	0.92460255
3	004A19	4.24439	-0.04527	0.838014	0.92420733
4	005A18	5.290351	-0.05706	0.801552	0.90552945
5	009A13	4.023873	-0.04282	0.845876	0.92814512
6	028A34	0.390679	-0.004	0.984149	0.9930236
7	028A35	2.126466	-0.02218	0.91603	0.9620274
8	028A37	1.398305	-0.01447	0.944148	0.97503027
9	028A41	0.427793	-0.00438	0.982653	0.99236084
10	030A20	1.286752	-0.0133	0.948514	0.97702228

Table 5. Analysis of the proposed method in comparison to existing methods.

S.no	Method	Classification Percentage
1	Proposed Method _Co-occurrence Features on FWNPM	99.2
2	Motif Shape Primitives on -FWNP[6]	99
3	Shape primitives on Texton-LBP[13]	95
4	Classification with Geometrical Features[14]	94.5
5	Classification using neural networks[15]	80

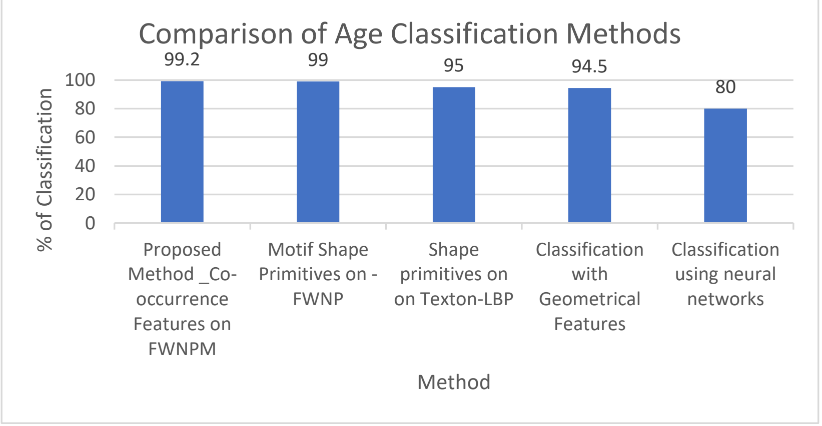

Fig.4. Comparison with other methods

4. Conclusion

The proposed FWNP collects local textured details from a facial image to reduce the dimensionality of the image and the computational cost. Co-occurrence features are evaluated on FWNP. These features, along with the SVM classifier, are employed to effectively distinguish between two age groups for work sustainability. This method has been found to be simple and efficient. The proposed method demonstrated a high classification rate when compared to other current methods. Future research should be devoted to the development of methods with shape features.

References

1. Iga, R., Izumi, K., Hayashi, H., Fukano, G., Ohtani, T., *A gender and age estimation system from face images*, In SICE Annual Conference in Fukui, (2003)
2. Lanitis, A., *On the significance of different facial parts for automatic age estimation*, In 14th International Conference on Digital Signal Processing, (2002)
3. Kwon, Y., Lobo, N., Computer Vision and Image Understanding. **74**, (1999)
4. Horng, W., Lee, C., Chen, C., Tamkang Journal of Science and Engineering. **4**, (2001)
5. P. C. S. Reddy, S. G. Rao, G. R. Sakthidharan and P. V. Rao, *Age Grouping with Central Local Binary Pattern based Structure Co-occurrence Features,* In International Conference on Smart Systems and Inventive Technology (ICSSIT), (2018)
6. Chandra Sekhar Reddy, P., Vara Prasad Rao, P., Kiran Kumar Reddy, P., Sridhar, M., *Motif Shape Primitives on Fibonacci Weighted Neighborhood Pattern for Age Classification*, In Soft Computing and Signal Processing . Advances in Intelligent Systems and Computing, vol 900. Springer, Singapore, (2019)
7. Chandra Sekhar Reddy P , Sakthidharan G, Kanimozhi Suguna S, Mannar Mannan J, Varaprasada Rao P, International Journal of Engineering and Advanced Technology. **8,** (2019)
8. Beena Bethel, G.N., Rajinikanth, T.V., Viswanadha Raju, S., *Enhancement of anisotropic diffusion filtered cardiac MR images using contrast-based fuzzy approach,* Lecture Notes in Networks and,119, (2020)
9. Kumar, S.K., Reddy, P.D.K., Ramesh, G., Maddumala, V.R. , Traitement du Signal, **36**, (2019)
10. Gajula Ramesh, Anusha Anugu, Karanam Madhavi, P. Surekha, *Automated Identification and Classification of Blur Images, Duplicate Images Using Open CV.* In ICAICR 2020, Communications in Computer and Information Science, vol 1393. Springer, Singapore, (2020)
11. M. Wiernik, B., S. Ones, D. and Dilchert, S, Journal of Managerial Psychology, **28**, (2013)
12. RM Haralick, K Shanmugan and I Dinstein, IEEE Transactions on Systems, Man, and Cybernetics. **3**, (1973)
13. P.Chandra Sekhar Reddy, B. Eswara Reddy and V. Vijaya Kumar, International Journal of Image, Graphics and Signal Processing. **4**, (2012)
14. M. Chandra Mohan, V. Vijaya Kumar and B. Sujatha, International Journal of Signal and Image Processing. **1**, (2010)
15. T. Kanno, Classification of age group based on facial images of young males by using neural networks. IEICE Transactions on Information and Systems. **84**, (2001)