

Age Group Estimation and Gender Recognition Using Face Features

Prajakta A. Mélange¹, Dr. G. S. Sable²

¹PG Student, Department of Electronics & Telecommunication Engineering, Maharashtra Institute of Technology, Aurangabad, India

²Professor, Department of Electronics & Telecommunication Engineering, Maharashtra Institute of Technology, Aurangabad, India

Corresponding Author: Prajakta A. Mélange

-----ABSTRACT-----

Recognition of the most facial variations, such as identity, age and gender has been extensively studied. This paper concerns with providing a methodology to estimate age group and gender using face features. This process involves four stages: Pre-processing, Face Normalization, Feature Extraction and Classification. The geometric features of facial images like wrinkle geography, face angle, left eye to right eye distance, eye to nose distance, eye to chin distance and eye to lip distance are calculated. Based on the texture and shape information age classification is done. Age ranges are classified dynamically depending on number of groups using SVM classifier algorithm. This paper can be used for predicting future faces, classifying gender, and expression detection from facial images.

KEYWORDS - Face detection, Feature extraction, Gaussian filter, LBP, Matlab, SVM

Date of Submission: 22-06-2018

Date of acceptance: 07-07-2018

I. INTRODUCTION

The face recognition is one of the biometric methods to identify individuals by features of the face. The biometric has a significant advantage over traditional authentication techniques as the biometric characteristics of the individual are unique for every person. A problem of personal verification and identification is an actively growing area of research. Face images are being increasingly used as additional means of authentication in applications of high security zone. In this paper, effective age group estimation using face features like texture and shape from human face image are proposed. For better performance, the geometric features of facial image like wrinkle geography, face angle, left to right eye distance, eye to nose distance, eye to chin distance and eye to lip distance are calculated. In this paper we have collected real time images distributed as per age group. Support Vector Machine (SVM) classifier & Local Binary Pattern (LBP) is used for age & gender classification.

II. LITERATURE SURVEY

Face recognition and the classification of the age and gender of face objects are two interesting field of research in this area. In this paper we provide a brief review of some of existing methods in face, gender and age recognition.

Table 2.1: Literature Survey Summary

Sr.no	Title of paper	Authour	Publication	Technique used
01	Age and Gender Estimation of Unfiltered Faces	Eran Eidinger, Roee	IEEE TRANSACTIONDEC. 2014	Robust face alignment technique, SVM
02	Automated Estimation of Human Age, Gender and Expression	Yaoyu Tao	Stanford, CA 94305, USA taoyaoyu@stanford.edu	LBP & Gabor filter LDA algorithm
03	Comparison of Recent Machine Learning Techniques for Gender Recognition	Joseph Lemley Sami Abdul-Wahid Dipayan	Central Washington University Ellensburg, WA, USA MAICS 2016	Feature extraction techniques: PCA & HOG. Gender classification methods

	from Facial Images	Banik		
04	Age Group Estimation using Face Features	Ranjan Jana, Debaleena Datta, Rituparna	(IJEIT) Volume 3, Issue 2, August 2013	K-means clustering algorithm. PCA, LDA.
05	Partial Face Recognition: Alignment-Free Approach	Shengcai Liao, Anil K. Jain, Fellow, IEEE and Stan Z. Li	IEEE transactions on pattern analysis	PCA + LDA & LBP Canny edge detector
06	Gender Recognition and Age-group Prediction: A Survey	Mr. Brajesh Patel. Mr. Raghvendra	ISSN:2319-7242 Volume 3 Dec.2014	Algorithm: SVM Adaboost
07	Gender Recognition from Model's Face SVM Algorithm	Deepak Deshmukh	(IJETT)-Volume 10 Number 1 - Apr 2014	Support vector machine & Fisher algorithm
08	Combining Face and Iris Biometrics for Identity Verification	Yunhong Wang, Tieniu Tan, Anil K. Jain	Center for Biometrics Authentication & testing	Algorithms:PCA, ICA ,LDA. Eigenface method as face matcher
09	An Image Mining System for Gender Classification & Age Prediction Based on Facial Features	Ms.Dhanashri Shirkey , Prof.Dr.S.R. Gupta	e-ISSN: 2278 Volume 10, Issue 6 (May. - Jun. 2013)	Adaboost tool for feature selection. Viola's method
10	A Discriminative Model for Age Invariant Face Recognition	Zhifeng Li, Member, IEEE, UnsanAnil	IEEE transactions on information forensics	Multifeature discriminant analysis (MFDA)
11	Face Recognition Based on Improved SIFT Algorithm	Ehsan sadeghipo Nasrollah sahragard	(IJACSA) Vol. 7, No. 1, 2016	Improved SIFT descriptor using Gabor
12	Texture-based estimation of age and gender from wild conditions	Aswathy Unnikrishnan, Dr. Jubilant	(ICETEST - 2015)	Dropout support vector machine Both Gabor & LBP features

III. SYSTEM DEVELOPMENT

The face images of persons are captured by means of a android camera (SAMSUNG Galaxy on 8-SM-J710FN) and some images are collected from net data set images. This paper proposed a novel and effective age group estimation using face features from human face images. This process involves three stages: Pre-processing, Normalization, Feature Extraction, and Classification.

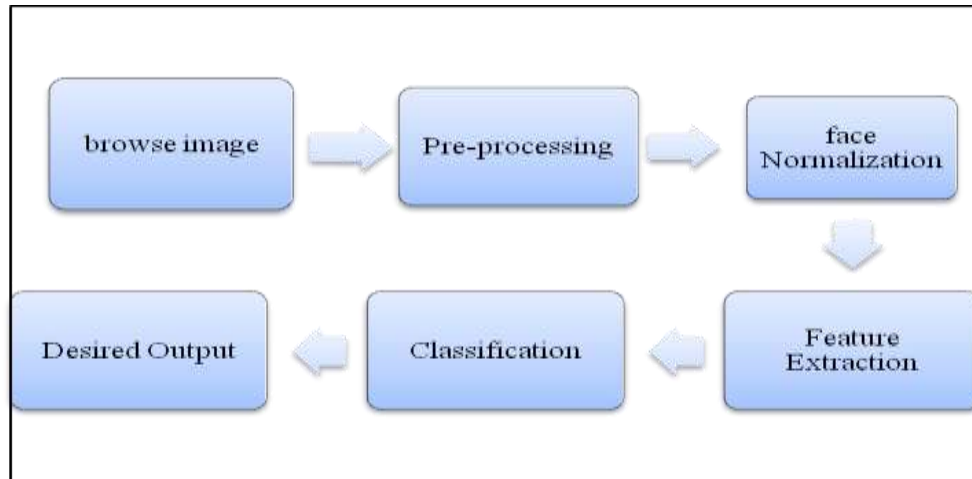


Fig.3.1: Proposed Block Diagram

1. Pre-processing

The face image of a person is captured by a digital camera as shown in Fig.3.1. Pre-processing includes three steps as detecting the image, converting to gray scale & noise reduced image.



Fig.3.2: Pre-processing stage

The color image is converted into gray scale image. The Matlab code is used for conversion of RGB to Gray scale image represented in binary digits 0 and 1. There are different types of filtration methods used for noise reduction techniques. Gaussian filtering method is used for noise reduction.

2. Normalization

In normalization process the system crop the detected rectangular face area as shown in Fig.3.2 using Matlab in-built object function. Then, detect the eye pair, mouth, nose, and chin. It gives the specific images of left eye, right eye, left eyebrow, right eyebrow, mouth i.e. image of lips & also detects chin hair line part of face image and also gives the nose image.



Fig.3.3: Normalization

3. Feature Extraction

A combination of global and grid features are extracted from face images. The global features such as distance between two eye balls, eye to nose tip, eye to chin, and eye to lip is calculated in Fig.3.3 using four distance values, four features are calculated.

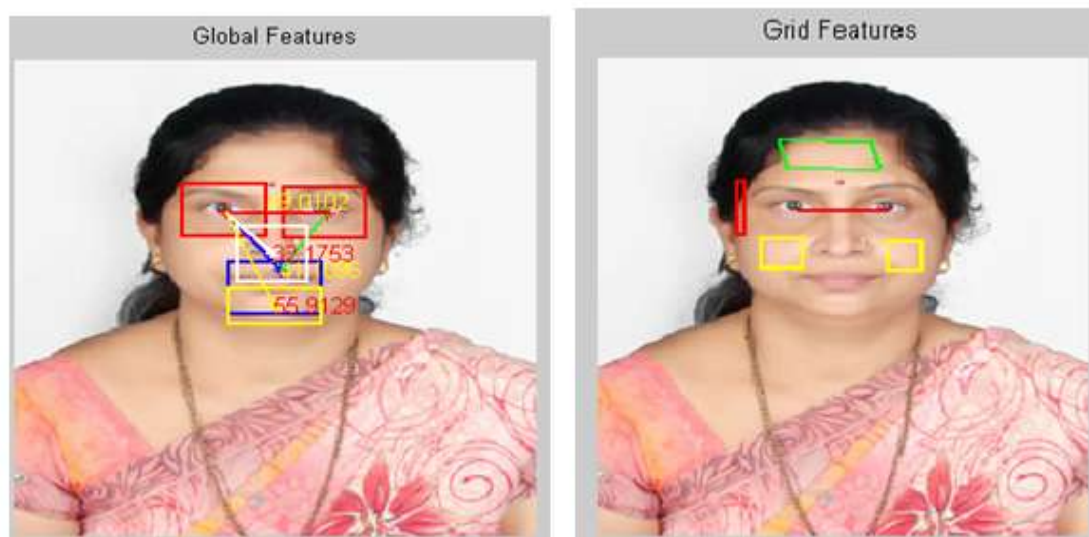


Fig.3.4: Feature Extraction

Four features F1, F2, F3, and F4 denotes the global features and the feature F5 is calculated for grid features.

The canny edge detection technique is used for finding the grid features. The four features F1, F2, F3, and F4 are calculated as follows:

$$F1 = (\text{distance from left to right eye ball}) / (\text{distance from eye to nose})$$

$$F2 = (\text{distance from left to right eye ball}) / (\text{distance from eye to lip})$$

$$F3 = (\text{distance from eye to nose}) / (\text{distance from eye to chin})$$

$$F4 = (\text{distance from eye to nose}) / (\text{distance from eye to lip})$$

F6 = the angle between right eyeball, mouth point, and left eye ball in face image.

Using the Grid features of face image, feature F5 is calculated. It is entirely based on wrinkle geography in face image. The grid feature includes forehead portion, eyelid regions, upper portion of cheeks and eye corner regions as shown in Fig.1(d). To calculate feature F5, the following steps have to be followed: The color face image is converted into gray scale image. Then canny edge detection technique is applied on gray scale face image. It gives a binary face image with wrinkle edges.

IV. CLASSIFICATION

Age ranges are classified dynamically depending on number of groups based on the above six features F1 to F6. Support vector machine (SVM) is used as age classifier technique. Age classification is done into 2, 3, and 4 age range groups shown in Table I. Using five features F1 to F5, age classification is done into 5 age range groups.

I. EXPERIMENTAL RESULTS

The required output is obtained after the classification process, thus the obtained desired output recognizes age and gender and is shown in the figure 4.1. Hence in this paper we worked out total five stages which give the age and gender identification.

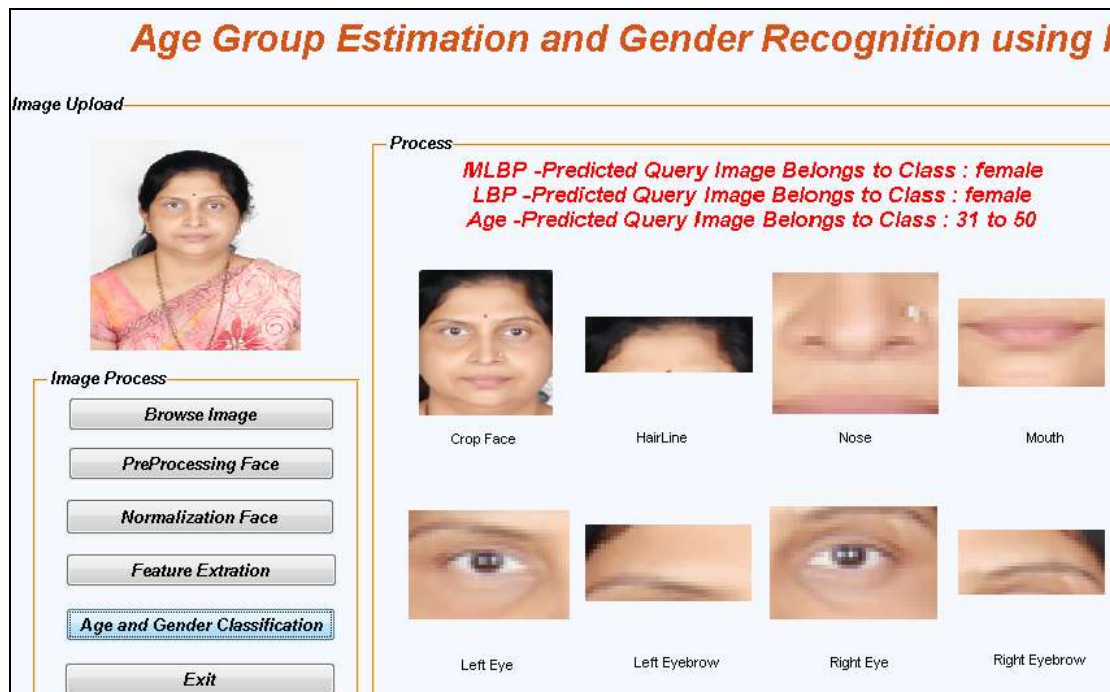


Fig.4.1: Desired output of age and gender

The recognition accuracy is given in equation as below:

$$\text{Recognition accuracy} = \frac{\text{No. of correct recognised face images}}{\text{Total no. of testing face images}} \times 100$$

1.True Recognition Accuracy (TRA)

Table 4.1: TRA for age group

Sr no.	Age group	% True accuracy
1	5-17	90%
2	18-30	100%
3	31-50	85%
4	51-70	70%
5	71-100	80%
True Recognition Accuracy		85%

Table4.2: TRA for gender

Sr No.	Class	% True accuracy	
		LBP	MLBP
1	Female	100%	80%
2	Male	90%	70%
True Recognition Accuracy		95%	75%

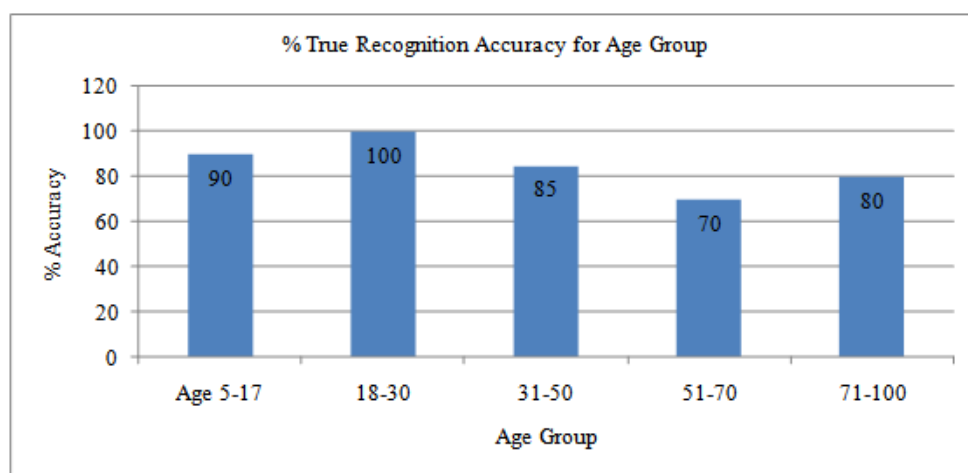


Fig.4.3: Graph of TRA for age group

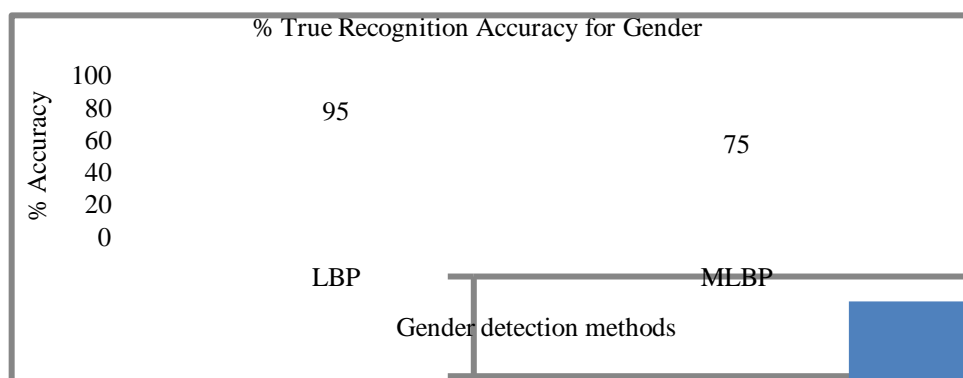


Fig.4.4: Graph of TRA for gender

V. CONCLUSION

Age, gender and other facial traits represent information important to a wide range of tasks. Our work leads us to the conclusion that wrinkle geography analysis has been the best procedure to estimate human age range of an individual. For proper eye and eyeball detection, face in the image should be without spectacle. Image should be of a straight frontal face. Image should contain single human face only. This paper works with 85% accuracy for age group clusters, and 95% accuracy for gender recognition. SVM classifier is used for age group estimation and we finalize LBP technique for gender identification

Here, we are primarily motivated by the observation that the amount of data available for the study of a computer vision problem, in particular the problems considered here, can have an immense impact on the machine capabilities developed to solve it. In answer to this, we provide two contributions: a new and extensive data set and for the study of age and gender estimation, and a classification pipeline designed with an emphasis on making the most of what little data is available.

REFERENCES

- [1]. H. Ai and Z. Yang. Demographic classification with local binary patterns. *Advances in Biometrics*, 4642:464{473, August 2007.
- [2]. A.N.Akansu and R.A. Haddad. *Multiresolution Signal Decomposition: Transforms, Subbands, and Wavelets*. Telecommunications Series. Academic Press, 2001.
- [3]. A. Alahi, R. Ortiz, and P. Vandergheynst. Freak: Fast retina keypoint. In *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)* June 2012.
- [4]. F.A. Alomar, G. Muhammad, H. Aboalsamh, M. Hussain, A.M. Mirza, and G. Bebis. Gender recognition from faces using bandlet and local binary patterns. In *20th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 59{62, July 2013.
- [5]. P.N. Belhumeur, J.P. Hespanha, and D. Kriegman. Eigenfaces vs. sherefaces: recognition using class specific linear projection. volume 19, pages 711{720, Jul 1997.
- [6]. S. Belongie, J. Malik, and J. Puzicha. Shape matching and object recognition using shape contexts. volume 24, pages 509{522, Apr 2002.
- [7]. Wen bing Horng, Cheng ping Lee, and Chun wen Chen. Classification of age groups based on facial features. 2001.78
- [8]. Bernhard E. Boser, Isabelle M. Guyon, and Vladimir N. Vapnik. A training algorithm for optimal margin classifiers. In *Proceedings of the 5th Annual ACM Workshop on Computational Learning Theory*, pages 144{152. ACM Press, 1992.
- [9]. Roberto Brunelli and T. Poggio. Face recognition: features versus templates. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 15(10):1042{1052, Oct 1993.
- [10]. Len Bui, D. Tran, Xu Huang, and G. Chetty. Face gender recognition based on 2d principal component analysis and support vector machine. pages 579{582, Sept 2010.
- [11]. J. G. Wang C. Y. Lee, J. Li and W. Y. Yau. Dense sift and gabor descriptors-basedface representation with applications to gender recognition. *International Conferenc on Control Automation Robotics and Vision*, pages 1860{1864, December 2010.
- [12]. M. Calonder, V. Lepetit, M. Ozuysal, T. Trzcinski, C. Strecha, and P. Fua. BRIEF:Computing a Local Binary Descriptor Very Fast. volume 34, pages 1281{1298, 2012.}

BIOGRAPHIES AND PHOTOGRAPHS



Prajakta A. Mulange Student of MTech (ETC) 2ndYear, Maharashtra Institute of Technology, Aurangabad, India. BE (ETC) from Anuradha Engineering College, Chikhli in 2013. She has total 01 year teaching experience. She has published one paper in international journal.



Dr. G. S. Sable Professor and Head of Electronics & Telecommunication Engineering department at Maharashtra Institute of Technology, Aurangabad, India. PhD from Dr. Bababshab Ambedkar Marathwada University, Aurangabad. M.E. and B.E. from J. N. E. College, Aurangabad. He has more than 40 publications to his credit and has been active in research and development. He has more than 14 years of teaching experience. He is a member of editorial advisory board of the different Journals. He is Authors of the book *Microprocessor and Computer Organization* for the second year CSE/IT Branch students and the member of the IEEE, ISTE, and IACSIT. He is Member of 32(6) a Malpractice Committee of Dr. Bababshab Ambedkar Marathwada University, Aurangabad.

Prajakta A. Méléange "Age Group Estimation and Gender Recognition Using Face Features." *The International Journal of Engineering and Science (IJES)* 7.7 (2018): 01-07