Generating efficient classifiers using facial components for age classification

Sreejit Panicker* and Smita Selot

SSTC,
Junwani Bhilai, Chhattisgarh, 491001, India
Email: sreejit.bhilai@gmail.com
Email: smitaselot504@gmail.com
*Corresponding author

Manisha Sharma

Bhilai Institute of Technology Durg,
Chhattisgarh, 491001, India
Email: manishasharma1@rediffmail.com

Abstract: Ageing a natural phenomenon, happens with time and becomes evident as a person grows. An individual undergoes various changes as age progresses. This is noticeable by his or her facial structure and texture which changes as growth accelerate. Facial growing is a standard happening that is sure, and differs from individual to individual subject on the conditions and living susceptibility. Uses of age assertion are seen in areas like Forensic science, security, and furthermore to decide wellbeing of an individual. Facial parameters used for age characterisation can be either structural or textural. In this paper, we have used statistical methodologies for feature extraction. In structural, facial development is considered for characterisation, by figuring the Euclidean separation between the different points of interest on the facial image. The experimental results are significant and remarkable.

Keywords: ageing; age estimation; texture.

Reference to this paper should be made as follows: Panicker, S., Selot, S. and Sharma, M. (2018) 'Generating efficient classifiers using facial components for age classification', *Int. J. Image Mining*, Vol. 3, No. 1, pp.38–47.

Biographical notes: Sreejit Panicker received his MCA from Madurai Kamaraj University, Madurai, Tamil Nadu, in 2002, and an ME in Computer Technology and Application from Shri Shankaracharya College of Engineering and Technology, Bhilai, Chattishgarh in 2009. He is working as an Associate Professor in the Department of Computer Application, Shri Shankaracharya Technical Campus, Bhilai Chattishgarh, since 2002. Currently pursuing his PhD from Bhilai Institute of Technology, Durg. His research interest includes pattern recognition, network security and image processing.

Smita Selot is a Professor and Head in the Department of Computer Applications, Shri Shankaracharya Technical Campus, Bhilai, has 20 years of teaching experience in technical institutes. She completed MCA from Government Engineering College, Jabalpur and was awarded PhD in 2013 by Chhattisgarh Swami Vivekanand Technical University, Bhilai. She has 32 papers in national and international journals and conferences to her credit.

Her research interest includes natural language processing, soft computing and pattern recognition. She is a life fellow of Indian Society for Technical Education and Computer Society of India.

Manisha Sharma received her BE in Electronics and Telecommunication from Govt. Engineering College Bhopal and completed her post graduation from Government Engineering College Jabalpur .She received her PhD from CSVTU, Bhilai in 2010. She has to her credit, more than 60 papers in various international & national journals and conferences. With more than 20 years of teaching and research experience she is currently serving as a Professor and Head in the Department of Electronics and Telecommunication, Bhilai Institute of Technology, Durg. Her areas of interest include, image and video processing, information security and digital watermarking.

This paper is a revised and expanded version of a paper entitled 'Fusion of structural and textural facial features for generating efficient age classifiers' presented at *ICIA16*, Pondicherry Engineering College, TN, 25–26 August, 2016.

1 Introduction

The present expertise in information processing via computer systems has enormously reduced the complexity of Human–Machine interaction. The ageing starts at the age of 25, when the first signs become visible on the facial skin. In the very beginning a fine line appears which gradually turn to wrinkles, and over time it loses its volume and density that makes it more noticeable.

Understanding the anatomy of facial ageing, the surface and subsurface known as epidermis, dermis and subcutaneous layer change its structural form in multiple layers which includes fat and muscle. In the process of ageing, skin changes its texture such as thinner skin, drier skin, less elastic skin, wrinkle and reduction in collagen. To achieve our goal we have created a database of feature set, used to train and test the proposed; also a proper ANN model is built to address the problem.

Applying machine learning for age estimation is a complex and challenging task. Every individual has his own rate of ageing, which is purely dependent on various factors which include fitness, living habits, work environment and social surroundings. Ages show varied forms of ageing, thus finding the age of a human through facial features using different approaches in computer vision and pattern recognition and gained significant importance (Hewahi et al., 2010; Othman and Adnan, 2014; Panicker et al., 2014). The changes in shape (craniofacial growth) are noticeable in early years to teens; gradually the size of the face gets larger in later years. The major growth change identifiable is skin ageing (texture change) which happens while ageing from youth to adulthood.

Ageing is a continuous and streamlined process which occurs in human face as age progress and with times gradually becomes evident by the facial parameters that influence the ageing factor. Thus, facial ageing is uncontrollable and personalised. Males and females ageing patterns are unlike, mainly because of makeup used by females that are expected to show younger appearances.

With technology advancement, determining age is the future need for various real-world applications. Ageing is a usual happening which shows signs of the changes, more apparent in context to facial growth. Facial features are considered as parameters for gender identification and expressions, with these feature researchers have contributed their work in this field. The age estimation and classification with facial parameter has increased its significance among researchers.

The paper is agreed as follows: Section 2 discusses the role of researchers in terms of feature extraction and classification problem. Section 3 is about the method used for feature extraction by using the statistical technique. Section 4 shows the trial results by placing appropriate the method. Section 5 provides the conclusion of the result.

2 Related work

Duong et al. (2011) proposed a combination of both global and local features using active appearance model (AAM) and local binary pattern (LBP) approach, in which LBP for the images in the face and gesture recognition research network (FGNET) was used for binary classifier to identify youth from adults using Support Vector Machine (SVM).

Ramanathan and Chellappa (2008) proposed an image gradient based texture transformation function that distinguishes facial wrinkles often seen during ageing. The rate of wrinkles visible for individuals varies from person to person. Jana and Saha (2014) proposed a technique, which provides a robust method that validates the age group of individuals from a set of different aged face images. The vital features such as distances between various parts of the face, analysis of wrinkle characteristics and computation of face position are observed.

Yen and Nithianandan (2002) proposed a methodology based on the edge density distribution of the image. In the pre-processing stage, a face is estimated to an ellipse, and genetic algorithm is applied to look for the finest ellipse region to match. In the feature extraction stage, a genetic algorithm is applied to find out the facial features, which include the eyes, nose and mouth, in the earlier defined sub-regions.

Jana et al. (2013) provide a method to calculate the age of human by analysing wrinkle area of facial images. Wrinkle characteristics are detected and features are extracted from facial images. Depending on wrinkle features, the facial image is grouped using fuzzy c-means clustering algorithm.

Lanitis et al. (2004) generated a model of facial appearance that uses statistical methods. It was further used as the source for generating a set of the parametric depiction of face images. Based on the model classifiers were generated that accepted the form of representation given for the image and computed an approximation of the age for the face image. With the given training set, based on different clusters of images, classifiers for every age group were used to estimate age. Thus as given requirement in terms of age range, the most appropriate classifier was selected so as to compute accurate age estimation.

Ramesha et al. (2010) proposed age classification algorithm with extracted features using small training sets which gives improved results even if one image per person is available. It is a three-stage process which includes preprocessing, feature extraction and classification. The facial features are identified using canny edge operator for detecting facial parts for extraction of features, and are subjected to classification using Artificial Neural Network.

Gu et al. (2003) proposed automatic extraction of feature points from faces. A possible approach to find the eyeballs, close to and distant corners of eyes, the centre of nostril, and corners of mouth was adopted. Suo et al. (2010) it represented a compositional model using hierarchical And – Or graph that shows face in a particular age group. In this method, the And nodes disintegrate a face into parts to reveal details (e.g., hair, wrinkles, etc.) crucial for age observation and Or nodes signify array of faces by applying different selection. The performance of ageing model and age estimation algorithm is validated using statistical analysis.

3 Methodology

3.1 Global feature extraction

The input image is cropped and then subjected to pre-processing to have uniformity in size and shape of the images. After these pre-processing done to the input image we compute the mean value within the cropped image area. The cropped image is then applied for feature extraction by using facial parameters.

The facial model in our approach Geometric Facial Measurement Model (GFMM) has various landmark points which comprise the feature set for further analysis using ANN classifiers as shown (see Figure 1).

The facial model with parameters is revealed in (see Figure 2). The details of each feature ID is elaborated in (Table 1).

Figure 1 Diagram for performing GFMM

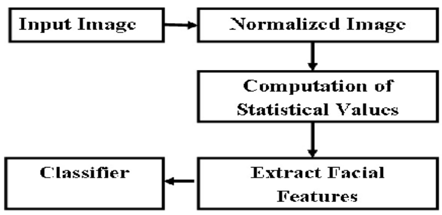


Figure 2 Facial feature parameters (see online version for colours)

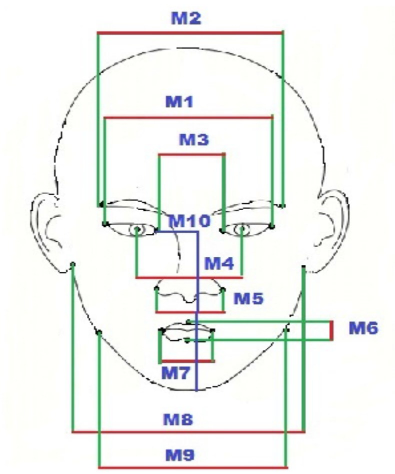


Table 1 Illustrates facial features in the model

Feature Id	*Feature parameter*
M1	Extreme ends of the left and right eye
M2	Extreme ends of the left and right eyebrow
M3	Left and right eye points between nose
M4	Between the left and right iris
M5	Nose end points
M6	Lips vertical measurement
M7	Lips horizontal measurement
M8	Ear points left and right
M9	Cheek points left to right
M10	Vertical measurement from the nose

These facial features are used to compute the distance between the given points for different persons in our FGNET facial ageing database. The computed values are then structured in different groups for age classification.

3.2 Mathematical formulations

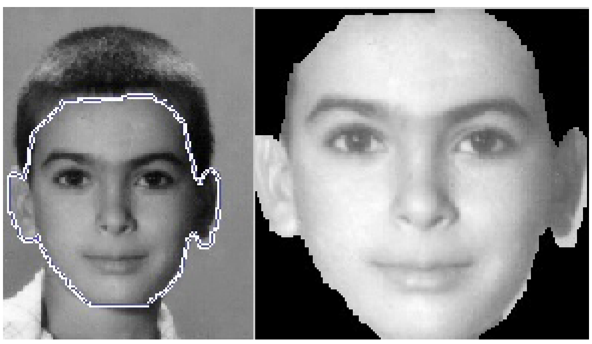
After we cropped the image it is subjected to normalisation which is further processed to estimate the area. The value is a scalar that corresponds to the entire pixel number in the normalised image, at times it may not be the same because pixels with varied patterns are weighed differently. We use these values to compute Mean, each row or column of the input with the vectors of a particular dimension of the input, or complete.

The Euclidean distance is the straight line distance between two points in Euclidean space. The Euclidean distance between points p and q is the length of line segment connecting them in the plane with coordinates (x, y) and (a, b) is given by

$$\text{dist}((x, y), (a, b)) = \sqrt{}\,(x - a)^2 + (y - b)^2. \tag{1}$$

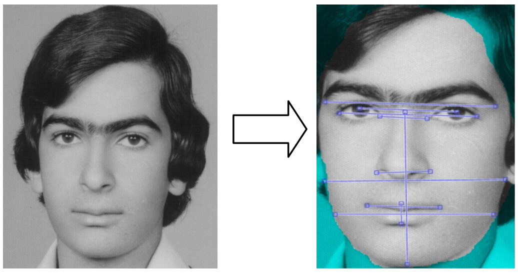
The approach used is implemented to FGNET ageing database. The GFMM is a graphical based implementation for feature extraction from the input image. The original input image and normalised image is shown in (Figure 3).

Figure 3 Cropped and normalised image for processing



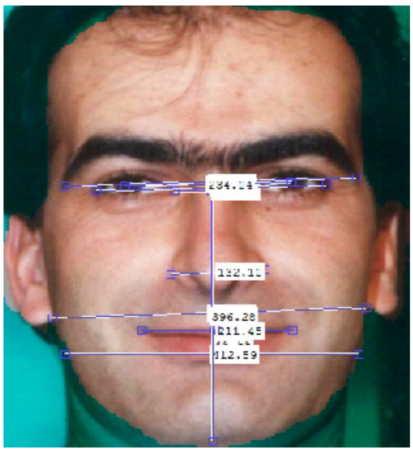
The normalised image is subjected to feature extraction here the distance between the points given in the feature ID is selected. After plotting all the facial feature parameters the values are computed for age classification problem. Figure 4 shows the facial feature parameters with their values.

Figure 4 Facial feature extraction (see online version for colours)



The computed values are plotted for further analysis of the feature which is considered in different age groups (Figure 5). Broadly four groups are identified in which different images from FGNET database are subjected to further classification.

Figure 5 Facial feature extraction by GFMM (see online version for colours)



3.3 Database for ageing

The FG-NET is a database of face images of persons at their different ages. FG-NET is widely preferred for age-related research works because it contains 1002 images of high-resolution colour or grey scale for performing various tasks. The age of persons in database varies from 0 to 69 years in chronological order of their ageing. It comprises of 82 multiple race images with a difference of lighting, pose and different expressions. The main effort to develop such a database was to help the researchers who perform various operations on facial image to study the ageing effects. The database is available for free access for research purpose.

4 Experimental results

4.1 Training with FGNET dataset

In training images of different subjects with varying ages, all age groups are considered. Four groups are classified as Child(C), Young (Y), Middle Aged (M) and Older (O). The extracted features are provided to Weka tool for machine learning. The preprocessed training dataset is trained using multilayer preceptron classifier. The result of training dataset is shown in Table 2. Further, the saved model is used to perform classification using same classifier for test dataset. The result of test dataset is shown in Table 3.

The corresponding graph for the training data against Table 2 is shown in Figure 6 that shows the classification of different classes for the given dataset. The plotted graph describes the training dataset accuracy details for the various paramaters, represented by different symbols for all the four groups.

Table 2 Detailed accuracy by class for the training dataset

TP rate	*FP rate*	*Precision*	*Recall*	*F measure*	*MCC*	*ROC area*	*Class*
1.000	0.018	0.955	1.000	0.977	0.968	1.000	c
0.935	0.089	0.879	0.935	0.906	0.839	0.973	m
0.889	0.052	0.842	0.889	0.865	0.822	0.959	y
0.333	0.000	1.000	0.333	0.500	0.562	0.862	o
0.895	**0.054**	**0.901**	**0.895**	**0.884**	**0.849**	**0.968**	**Weighted average**

Table 3 Detailed accuracy by class for the test dataset

TP rate	*FP rate*	*Precision*	*Recall*	*F measure*	*MCC*	*ROC area*	*Class*
1.000	0.000	1.000	1.000	1.000	1.000	1.000	c
0.900	0.067	0.900	0.900	0.900	0.833	0.993	m
0.857	0.056	0.857	0.857	0.857	0.802	0.960	y
1.000	0.000	1.000	1.000	1.000	1.000	1.000	o
0.920	**0.042**	**0.920**	**0.920**	**0.920**	**0.878**	**0.986**	**Weighted average**

Tp: Number of true positive case.

Fp: Number of false positive case.

MCC: Matthews correlation coefficient.

ROC: Receiver operating characteristics.

In the same way, depicting the graph for test dataset, that shows the accuracy for different classes of ageing as a weighted average. The table values depict the overall accuracy of the system trained. The plot is shown in Figure 7.

Figure 6 Plot against the training dataset of facial feature extracted (see online version for colours)

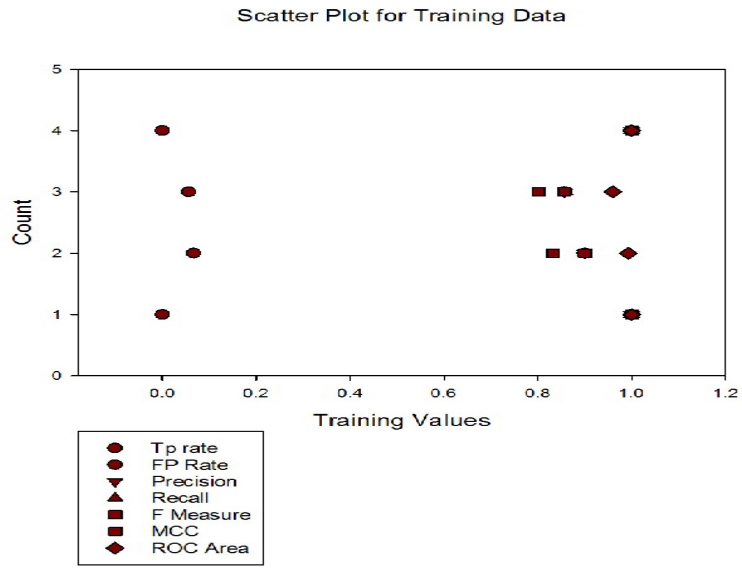
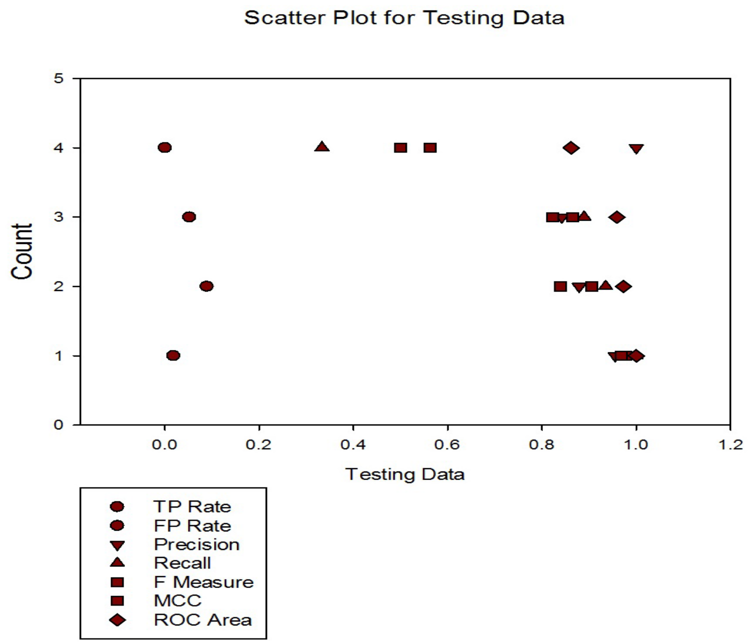


Figure 7 Plot against the test dataset facial feature extraction (see online version for colours)



For further analysis of the values generated against the training and test dataset, a graphical notation is shown in Figure 8.

Table 4 shows the evaluation parameters and the corresponding values while training the test dataset using the stored model for generating the classifiers.

Figure 8 Plot for the evaluation of training and test datasets (see online version for colours)

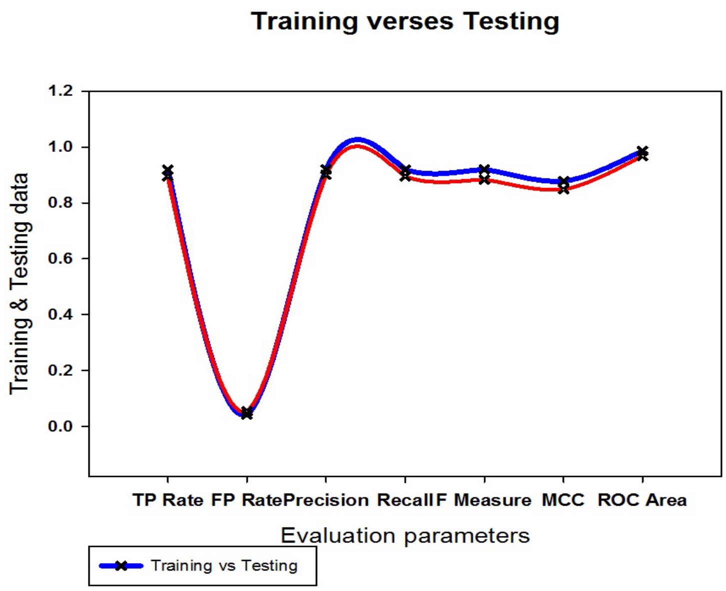


Table 4 Evaluation criteria and result for the test dataset

Evaluation parameters	*Values*
Correctly classified instances	92%
Incorrectly classified instances	8%
Mean absolute error	0.1193
Root mean squared error	0.199
Kappa statistic	0.8853

5 Conclusion

The proposed methodology is based on distance vector for extracting global facial features for age classification. The method of extracting facial parameters used here is different in comparison to other methods proposed previously. After performing pre-processing of the images in FGNET database, includes resizing and filtering to improve the competence of the classifier. A relative study has been done between different age group to evaluate the output of the proposed system. It is obvious from the output projected that the given system performs nearer to the human's assessment to classify age. In the testing phase, we found that the accuracy of the classification for various age groups is 92, thus efficiency is larger in context to the previous results. On analysing the computed statistics it's evident from the study that performance of the system is remarkable.

Acknowledgements

I extend my sincere thanks for the support and valuable guidance given by the professors, in the Department of Computer Application, Shri Shankaracharya Technical Campus, Bhilai and my research centre at Bhilai Institute of Technology, Durg, Chhattisgarh.

References

Duong, C.N., Quach, K.G., Luu, K., Le, H.B. and Karl, R. (2011) 'Fine tuning age-estimation with global and local facial features', *IEEE Int. Conf. ICASSP)*, pp.2032–2035.

Gu, H., Su, G. and Du, C. (2003) 'Feature points extraction from faces', *Image and Vision Computing*, Palmerston North, pp.154–158.

Hewahi, N., Olwan, A., Tubeel, N., Asar, S.E. and Sultan, Z.A. (2010) 'Age estimation based on neural networks using face features', *Journal of Emerging Trends in Computing and Information Sciences*, Vol. 1, No. 2, pp.61–67.

Jana, R., Datta, D. and Saha, R. (2013) 'Age group estimation using face features', *International Journal of Engineering and Innovative Technology (IJEIT)*, Vol. 3, No. 2, pp.130–134.

Jana, D. and Saha, R. (2014) 'Age estimation from face image using wrinkle features (*ICICT*)', *Elsevier Procedia Computer Science*, Vol. 46, pp.1754–1761.

Lanitis, A., Draganova, C. and Christodoulou, C. (2004) 'Comparing different classifiers for automatic age estimation', *IEEE Transactions On Systems, Man and Cybernetics–Part B: Cybernetics*, Vol. 34, No. 1, pp.621–628.

Othman and Adnan (2014) 'Age classification from facial images system', *IJCSMC*, Vol. 3, No. 10, pp.291–303.

Panicker, S., Selot, S. and Sharma, M. (2014) 'Human age estimation through face synthesis: a survey', *i-Manager's Journal on Pattern Recognition*, Vol. 1, No. 2, pp.1–6.

Ramanathan, N. and Chellappa, R. (2008) 'Modeling shape and textural variations in aging faces', *IEEE Int. Conf. Automatic Face and Gesture Recognition*, Amsterdam, pp.1–8.

Ramesha, K., Raja, K.B., Venugopal, K.R. and Patnaik, L.M. (2010) 'Feature extraction based face recognition, gender and age classification', *International Journal on Computer Science and Engineering*, Vol. 2, No. 1, pp.14–23.

Suo. J., Zhu. S.C., Shan. S. and Chen. X. (2010) 'A compositional and dynamic model for face aging', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 32, No. 3, pp.385–401.

Yen, G.G. and Nithianandan, N. (2002) 'Facial feature extraction using genetic algorithm', *Congress on Evolutionary Computation*, Honolulu, pp.1895–1900.