Feature Extraction based Face Recognition, Gender and Age Classification

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Abstract-The face recognition system with large sets of training sets for personal identification normally attains good accuracy. In this paper, we proposed Feature Extraction based Face Recognition, Gender and Age Classification (FEBFRGAC) algorithm with only small training sets and it yields good results even with one image per person. This process involves three stages: Pre-processing, Feature Extraction and Classification. The geometric features of facial images like eyes, nose, mouth etc. are located by using Canny edge operator and face recognition is performed. Based on the texture and shape information gender and age classification is done using Posteriori Class Probability and Artificial Neural Network respectively. It is observed that the face recognition is 100%, the gender and age classification is around 98% and 94% respectively.

Keywords: Age Classification, Artificial Neural Networks, Face Recognition, Gender Classification, Shape and Texture Transformation, Wrinkle Texture.

I. INTRODUCTION

A problem of personal verification and identification is an actively growing area of research. Face, voice, lip movements, hand geometry, odor, gait, iris, retina, fingerprint are the most commonly used authentication methods. All of these psychological and behavioral characteristics of a person are called biometrics. The driving force of the progress in this field is due to the growing role of the Internet and electronic transfers in modern society. Therefore, considerable number of applications is concentrated in the area of electronic commerce and electronic banking systems. The biometrics have a significant advantage over traditional authentication techniques due to the biometric characteristics of the individual are not easily transferable, are unique of every person, and cannot be lost, stolen or broken. The biometrics is a measurable physiological or behavioral characteristic of an individual used in personal identification and verification and the choice of the biometric solutions depends on user acceptance, level of security, accuracy, cost and implementation time.

Face recognition is one of the biometrics methods to identify individuals by the features of the face. Research in this area has been conducted for more than 30 years; as a result, the current status of the face recognition technology is well advanced. Many commercial applications of the face recognition are criminal identification, security system, image and film processing. Using a pre-stored image database, the face recognition system is able to identify or verify one or more persons in the data base. The face recognition for still images is categorized into three main groups such as Holistic, Feature based and Hybrid approach. The age and gender of a person is categorized by visual observation of images whereas it is difficult in the computer vision. The face is recognized by considering features viz., eye distance, nose distance, lip distance etc. The gender is classified by determining the features like mustache region, eye distance, total number of pixels of skin color etc. The age is identified using forehead region, right and left canthus, eyelid region etc.

Contribution: In this paper we proposed feature based FEBFRGAC algorithm. In Preprocessing color conversion, noise reduction and edge detection is performed to increase the quality of the face image by retaining the important characteristics. The geometric features from a facial image are obtained based on the symmetry of human faces and the variation of gray levels, the positions of eyes; nose and mouth are located by applying the Canny edge operator. The gender is classified based on posteriori class probability and age is classified based on the shape and texture information using Artificial Neural Network.

Organization: The paper is organized into the following sections. Section 2 is an overview of related work. The FEBFRGAC model is described in Section 3. Section 4 discusses the algorithm for FEBFRGAC system. Performance analysis and results of the system is discussed in Section 5 and Conclusions are discussed in Section 6.

II. RELATED WORK

M. D. Malkauthekar and S. D. Sapkal [1] Presented experimental analysis of classification of facial images. Facial images of different expressions and angles of two classes and three classes are used for classification. For two classes and three classes results are compared by Fisher Discriminant method and Euclidian distance is used for matching. G. Mallikarjuna Rao et al., [2] presented a Neural Network-based upright invariant frontal face detection system to classify the gender based on facial information. The reliability is depends on Pixel based and geometric facial features. The robustness of classification is depends on pi-sigma neural network and the cyclic shift invariance techniques. Zong X. Lin et al., [3] proposed fast vertical pose invariant face recognition module for intelligent robot guard. The vertical pose angle is evaluated by the height difference between the center of the eyes and the auriculocephalic sulcus of the pinna; earpiece rests on if glasses are worn. The vertical pose angle is derived by the arcsine function of the height difference over the earpiece length. Gabor Wavelet Transform (GWT) is adopted for feature extraction core of the original face recognition module.

Anil Kumar Sao and B. Yegnannarayna [4] proposed analytic phase based representation for face recognition to address the issue of illumination variation using trigonometric functions. To decide the weights to the projected coefficients in template matching eigenvalues are used. Jing Wu et al., [5] proposed gender classification using Shape from Shading (SFS). Linear Discriminant Analysis (LDA) is used based on the Principal Geodesic Analysis parameters to discriminate female and male genders of the test faces. SFS technique is used to improve the performance analysis of classification in gray scale face images.

Hui-Cheng Lain and Bao-Liang Lu [6] presented Multi-view gender classification considering both shape and texture information to represent facial images. The face area is divided into small regions, from which local binary pattern (LBP) histograms are extracted and concatenated into a single vector efficiently representing the facial image. Support Vector Machine (SVM) classifier is used for classification. Kazuya Ueki et al., [7] presented Age group classification using facial images under various lighting conditions. Carmen Martinez and Olac Fuentes [8] proposed a method to improve accuracy when only a small set of labeled examples are available using unlabelled data. Eigenface technique is applied to reduce the dimensionality of the image space and ensemble methods to obtain the classification of unlabelled data. Ensemble unlabeled data chooses the 3 or 5 examples for each class that are most likely belong to that class. These examples are appended to the training set in order to improve the accuracy and the process is repeated until no more examples to classify. The experiments were performed using k-nearest-neighbor, Artificial Neural Network (ANN) and locally weighted linear regression learning.

Ryotatsu Iga et al., [9] developed an algorithm to estimate Gender and Age using (SVM) based on features like geometric arrangement and luminosity of facial images. The graph matching method with GWT method is used to detect the position of the face. GWT features, such as geometric arrangement color, hair and mustache are used for gender estimation. GWT features viz., texture spots, wrinkles, and flabs are used for age estimation. Hui-Cheng Lain and Bao-Liang Lu [10] proposed Min-Max Modular Support Vector Machine (M^3- SVM) to estimate age. Facial point detection GWT and retina sampling method is used to extract features from face images. The task decomposition method is used in M^3-SVM to classify gender information inside age samples.

Ye Sun et al., [11] presented Embedded Hidden Markov Model (EHMM) to recognize face and age. The nonlinear relationship between the key feature points in the face and different ages of the same face are used to train EHMM to estimate ageing face. Allison C Lamont. et al., [12] presented a Study on recognition accuracy based on ageing effects. The Face recognition accuracy decreases with young faces when compared to old aged faces. Young H. Kwon and Niels Da Vitoria Lobo [13] presented visualized classification from facial images. The primary features of the face are eyes, nose, mouth, chin, virtual top of the head and sides of the face are computed using ratios to identify young adults and seniors. In secondary feature analysis the wrinkle index computation is used to distinguish seniors from young adults and babies. A combination of primary features and secondary features determine face into one of the three classes viz., babies, young adults and seniors.

Wen Bing Horng et al., [14] proposed a system to classify Age groups. Sobel edge operator is used to extract facial features and back-propagation Neural Networks are used to classify facial images into babies, young adults, middle aged adults and old adults. The Network uses the geometric features of wrinkle free facial images to identify baby images. The second Network uses wrinkle features of an image to classify into one of three adult groups. Andreas Lanitis et al., [15] proposed automatic simulation of ageing effect on face recognition system. The algorithm is used to predict facial appearance of persons/children who have missing for several years. The three formulations such as linear functions, quadratic functions, and cubic functions are used for ageing functions for individuals who provide age progressive images based on mean absolute error and standard deviation for over years.

Baback Moghaddam and Ming-Hsuan [16] developed an appearance based method to classify gender from facial images using nonlinear SVMs and compared their performance with traditional classifiers and modern techniques Radial Basis Function (RBF) networks and large ensemble-RBF classifiers, the difference in classification performance with low-resolution and the corresponding higher resolution images is one percent. Ara V. Nefian and Monson H. Hayes [17] described an EHMM for face detection and recognition using DCT coefficients. Zehang Sun et al., [18] proposed gender classification from frontal facial images using genetic feature subset selection. Principal Component Analysis (PCA) is used to represent each image as a feature vector in a low-dimensional space. Genetic algorithms select a subset of features from the low-dimensional representation by disregarding certain eigenvectors that do not seem to encode important gender information. Bayes, Neural Network, SVM, and LDA classifiers are used and compared using Genetic Algorithm feature subset selection.

Ming-Hsuan Yang and Baback Moghaddam [19] proposed Visual gender classification with low-resolution 'thumbnail faces (21-by-12 pixels) processed from 1755 images from the FERET face data base using SVM classifier and compared their performance of human test subjects on high and low resolution images. Shyh-Shiaw Kuo and Oscar E. Agazzi [20] presented a system based on the Hidden Morkov Modeling technique, which is capable of recognizing the key word embedded in poorly printed documents. In order to reduce the search space system uses the distinctive shape information of the expected word and all the other extraneous word, respectively. Two Bayesian distance of an input word with respect to the two models are calculated and compared to determine whether the input word is the expected keyword. Praseeda Lekshmi.V and M. Sasikumar [21] proposed a Face Recognition and Expression Analysis to separate skin and non-skin pixels. Skin regions are used to extract face regions which in turn used to analyze expressions. Input images are normalized to a uniform size and images are grouped based on expressions.

S.T Gandhe et al., [22] proposed Face Recognition using Contour Matching. The contour of a face images are considered for matching to recognize the face. Erno Makinen and Roope Raisamo [23] presented a study on gender classification with automatically detected and aligned faces. Gender classification methods: Multilayer Neural Network with image pixels as input, SVM with image pixels as input, SVM with LBP features as input and Discrete Adaboost with Harr-like features are considered for gender classification. SVM with image pixels as input achieved best classification rate. Xiaoguang Lu and Anil K. Jain [24] proposed 3D face matching in the presence of non rigid 3D face matching and pose changes in the test scans. The matching is performed by fitting the deformable model to a given test scan, which is formulated as minimization of a cost function.

Guillaume Heusch et al., [25] proposed LBP as an image preprocessing face authentication for illumination variations. LDA and HMM techniques are used for face authentication. Jang-Seon Ryu and Eung-Tae Kim [26] proposed pan-tilt-zoom (PTN) and fast face recognition algorithms used for face detection and tracking. DCT based HMM method is used for face recognition in Digital Voice recorder (DVR) system. Unsang Park et al., [27] proposed an automatic aging simulation technique for aging-invariant face recognition. 3D deformation model for crania facial aging 3D model is developed for pose and expression invariance. The age modeling method models grow pattern and adult aging based on the simulation of shape and texture information. Alice J. O'Toole et al., [28] presented face recognition algorithms surpass human matching faces over changes in illumination. On face matching task seven face recognition algorithms were compared with humans and found out whether pairs of face images under different illumination conditions, were pictures of the same person or of different people.

III. MODEL

Definitions

(i) *Preprocessing*: Face image is processed to obtain a transformed face image to increase the quality of the face image, retaining the important characteristics.

(ii) *Inter-ocular distance:* The distance between the right eye midpoint and left eye midpoint pixels in the face image.

(iii) *Lips to Nose:* The distance between nose tip to the midpoint of the lips pixel in the face image.

(iv) *Nose to Eyes:* The distance between Nose tip to the line joining two eyes midpoint of the pixels in the face image.

(v) *Lips to Eyes:* The distance between lips midpoint to the line joining two eyes midpoint of the pixels in the face image.

(vi) *Eccentricity of the face:* The shape of the face containing pixels in the face image.

(vii) *Ratio of dimension (D):* The ratio of width to height of the face image. The bounding box coordinates of the face image are determined and the width (Dx) and height (Dy) are computed using these coordinates.

$$D = \frac{Dx}{Dy} \tag{1}$$

(viii) *Width of the lips:* The distance between right endpoint of the lip to the left endpoint of the lip containing pixels in the face image.

(ix) *Skin color:* The total number of pixels containing in the face image.

(x) *Moustache region:* A strip region above the upper lip containing pixels in the face image.

(xi) *Lip region:* The region of the two fleshy Parts forming the edges of the mouth opening containing pixels in the face image.

(xii) *Eye tails:* The end region of eyebrows containing pixels in the face image.

(xiii) *Forehead:* The part of the face above the eyebrows containing pixels in the face image.

(xiv) *Canthus (Cheek):* The region on either side of the face below the eye containing pixels in the face image.

(xv) *Eyelid:* The region of the each upper and lower folds of skin which cover the eye containing pixels in the face image.

(xvi) *Nose wing:* The region which covered both sides of the nose containing pixels in the face image.

(xvii) *Mean:* The mean of a collection of pixels is their arithmetic intensity value average, computed by adding them and dividing by their total number and is given in Equation (2)

$$Mean = \sum_{i=1}^{n} \frac{a[i]}{n} \tag{2}$$

(xviii) *Variance:* A measure of the average distance between each set of data points and their mean value; equal to the sum of the squares of the deviation from the mean value is given in Equation (3)

$$Variance = \sum_{i=1}^{n} \frac{(a[i] - Mean)^2}{n} \tag{3}$$

(xx) *Standard Deviation (S.D):* Square root of variance is the standard deviation and is given in Equation (4).

$$S.D = \sqrt{Variance} \tag{4}$$

Block Diagram of FEBFRGAC

Figure 1 gives the block diagram of FEBFRGAC for verification of face, gender and age.

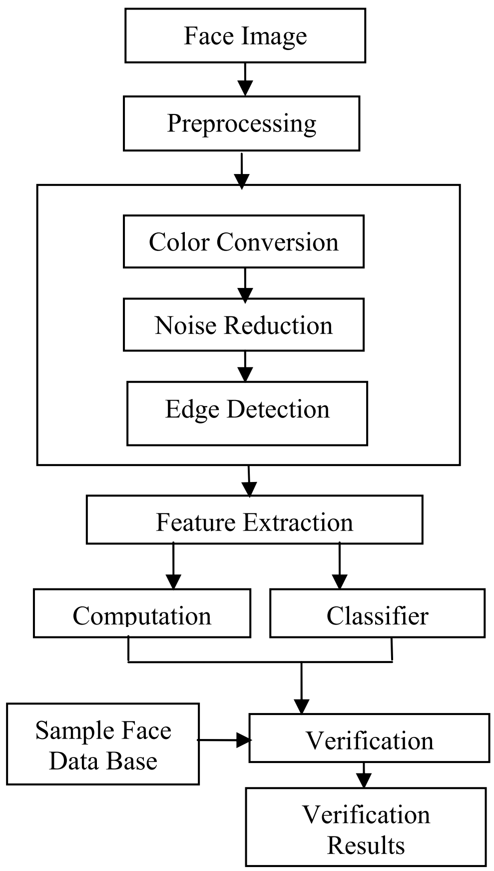


Figure 1. Block Diagram of FEBFRGAC

Face Image: The face image samples are collected from website as well as captured from the mobile phone and digital cameras.

Preprocessing:

(i) Color Conversion: An RGB color image is an MxNx3 array of color pixels is a triplet corresponding to the red, green and blue components of an RGB image at a specific spatial location. The data class of the component images determines their range of values. If an RGB image is of class double, the range of values is [0, 1]. Similarly, the range of values is [0,255] or [0, 65535] for RGB images of class unit8 or unit16 respectively. The number of bits used to represent the pixel values of component images determines the bit depth of an RGB image. The number of possible colors in an RGB image is $(2^b)^3$, where *b* is the number of bits in each component image. For 8-bit case, the number is 16,777,216 colors. Three dimensional RGB is converted into two dimensional gray scale images for easy processing of face image.

(ii) Noise reduction: A noise reduction filter is applied to the binary image for eliminating single black pixel on white background. 8-neighbors of chosen pixels are examined if the number of black pixels are greater than white pixels then it is considered as black otherwise white. Dirt on cameras or scanner lens, imperfection in the scanner lighting etc., introduces the noise in the scanned face image. A filtering function is used to remove the noise in the image and works like a majority function that replaces each pixel by its majority function.

(iii) Edge detection method: Point and line detections are important in image segmentation. Edge detection is far most common approach for detecting many discontinuities in intensity values. Canny edge detection finds edge by looking for local maxima of the gradient of f(x, y). The gradient is calculated using the derivatives of Gaussian filter.

The method uses two thresholds to detect strong and weak edges and includes the weak edges in the output only if they are connected to strong edges, i.e., to detect true weak edges. The local gradient is given by Equations (5) and (6)

$$G(x, y) = [Gx + Gy]^{1/2} \tag{5}$$

where G_x and G_y are the first derivatives of the function f(x, y), digitally.

$$\alpha(x, y) = \tan^{-1}(Gx / Gy) \tag{6}$$

where α(x, y) is edge direction shown in the Figure 2.

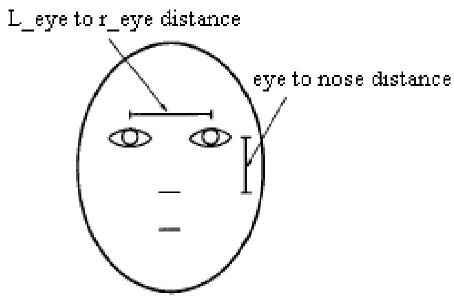
Figure 2. Canny edge detected image

Feature Extraction:

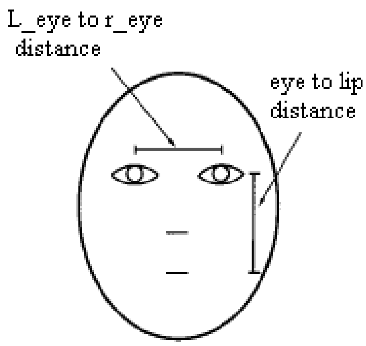
A combination of Global and Grid features are used to extract features. The Global features includes inter ocular distance, the distance between lips to the nose tip, the distance between nose tip to the line joining two eyes, the distance between lips to the line joining two eyes, eccentricity of the face, ratio of dimension, width of lips. The grid features used are the skin color, moustache region, lip region, eye tail, fore head, canthus, eyelid, and nose wing of the face image.

Computation:

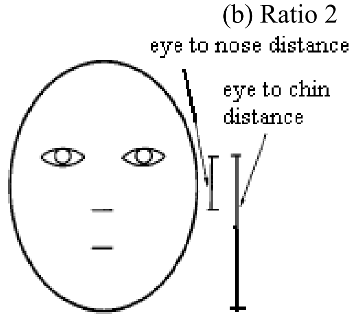
Facial feature ratios: The primary facial features are located to compute the ratios for age classification. Four ratios are calculated for facial face database comprising young aged, middle aged and old aged adults. Figure 3, a to d gives the ratios of l_eye to r_eye distance, eye to nose distance, eye to lip distance and eye to chin distance for feature extraction.



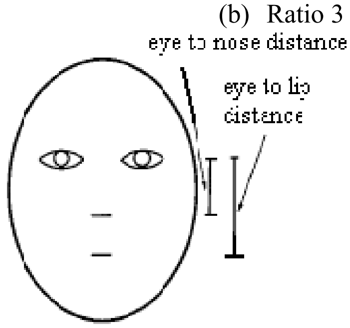
(a) Ratio 1



(b) Ratio 2



(b) Ratio 3



(d) Ratio 4

Figure 3. The four ratios used

The ratios suffer if the face is rotated in depth and measure needs to be adopted to compensate for rotation, before the ratios are computed. Ratio1, ratio2, ratio3 and ratio4 are computed using the Equations (7), (8), (9) and (10) respectively.

$$Ratio1 = \frac{L\_eye\ to\ r\_eye\ distance}{eye\ to\ nose\ distance} \tag{7}$$

$$Ratio2 = \frac{L\_eye\ to\ r\_eye\ distance}{eye\ to\ lip\ distance} \tag{8}$$

$$Ratio3 = \frac{eye\ to\ nose\ distance}{eye\ to\ chin\ distance} \tag{9}$$

$$Ratio4 = \frac{eye\ to\ nose\ distance}{eye\ to\ lip\ distance} \tag{10}$$

Wrinkle Analysis:

Figure 4 gives wrinkle geography, showing the regions of facial wrinkle of eyes, nose, mouth, cheek and sides of the face are located. Figure 5(a) Shows Young aged forehead region, 5(b) Middle aged forehead region, 5(c) Old aged forehead region 5(d) Young aged eyelid region, 5(e) Middle aged eyelid region, 5(f) Old aged eyelid region.

Figure 4. wrinkle geography

***Classifier**:* The posteriori class probabilities are used to classify the testing faces to one of the genders.

Let C= {C_i | i = female, male}, denotes the two gender classes, x denotes the feature of any testing face. Then according to Bayes Law, the probability that x is of class C_i is given in Equation (11)

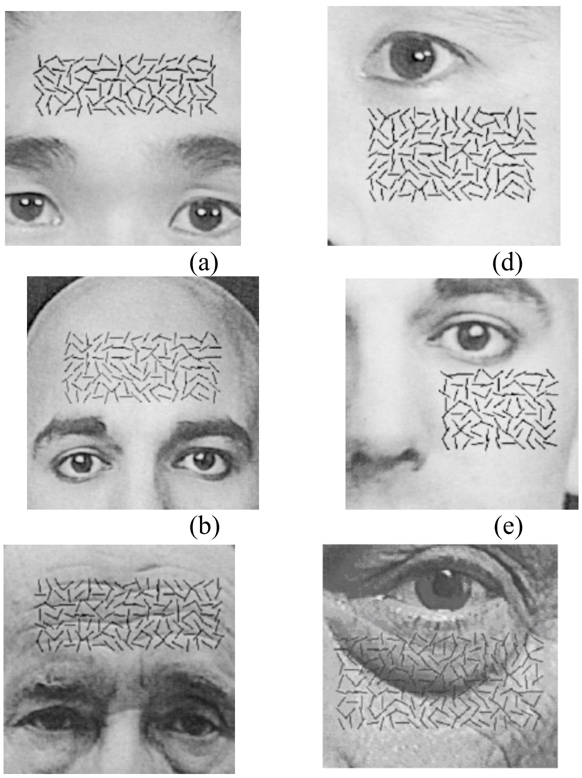
$$P(C_i/x) = \frac{P(x/C_i)\,P(C_i)}{\sum_{i=\ female\ ,\ male} P(x/C_i)} \tag{11}$$

We assume that the distribution of the gender is Gaussian and the mean and co-variance of class C_i is μ_i, σ_i. The priori probability is P (C_i) = 0.5 then,

$$P(x/C_i) = \frac{1}{(2\Pi\sigma_1{}^2)^{1/2}} \exp\left(\frac{-(x-\mu_i)^2}{2\sigma_1{}^2}\right) \qquad (12)$$

The posteriori probabilities P (C_{female} | x) and P (C_{male} | x) are computed by applying Equation (12) and priori probabilities into Equation (11).

If P (C_{female} | x) > P (C_{male} | x), then the face is classified as female and if P (C_{female} | x) < P (C_{male} | x), then the face is classified as male.



(a) (d) (b) (e) (c) (f)

Figure 5. Wrinkle of face images for different ages.

Figure 6 gives complete classifier for FEBFRGAC. For age estimation, two classifiers are prepared corresponding to gender. Each age classifier has been trained with male and female data. Based on the output of the gender classifier, suitable age classifier is used. The extracted feature of test face image is compared with the face database. If the extracted features of the test face image match with the sample face database then accepted as matching, otherwise, it is accepted as not matching.

C. Artificial Neural Networks (ANN):

ANN is the interconnection between the basic units called artificial neurons. An artificial neuron takes two inputs, multiplies them by a weight and adds them together. Each input link has an independent weight associated with it. If the sum of the weighted input's value is greater or equal to the threshold value, the output is equal to 1. If the sum is less than the threshold value, the output is 0. This is important, because it allows artificial neurons to compute the logical functions AND, OR and NOT. The artificial neurons to compute the three logic functions are combined to form artificial neural networks. ANN relies on its ability to adjust its weights in order to associate each piece of input to the corresponding desired output. This ability to adapt proves especially helpful for problems where there is a finite set of outcomes, but no realistic way to represent all possible inputs. In the context of FEBFRGAC verification, an ANN is created by combining artificial neurons into a structure containing three layers. The first layer consists of neurons that are responsible for inputting a face image sample into the ANN. The second layer is a hidden layer which allows an ANN to perform the error reduction necessary to successfully achieve the desired output. The final layer is the output layer wherein the number of neurons in this layer is determined by the size of the set of desired outputs, with each possible output being represented by a separate neuron.

Back propagation Networks (BPN): The process of determining the error rates of each neuron that impact the output is called back propagation. Figure 7 shows the typical structure of a back propagation Network. The neurons of the input layer are fully connected to the hidden layer and the outputs of the hidden layer are fully connected to the output layer. The error rate of one neuron affects the entire network. This procedure is crucial to the error minimization process, a process that will eventually lead to identification of the desired value. In back propagation a face image sample is propagated through the network producing an output. This is compared to the desired output, giving an error rate for the output layer. The error rates of a neuron being the function of the errors of units in the output layer, effects the layers below it. Due to this, the error propagates back to input layer through the hidden layer until the output reaches the desired value. Each neuron will make slight weight adjustments in order to minimize its error signal. The process is repeated for all the input values to be processed. In addition to the layered structure, BPN are also characterized as being feed-forward, which means that all the links in the network are unidirectional and the network is acyclic.

Training Method: The training of ANN is carried out in two parts. First, the feed-forward path is trained using the standard back propagation algorithm, until the feed-forward path is trained. The feedback path serves to alter the contribution that a given section of input makes to the outcome. This, in turn means that the feedback path must be taught to produce different signals depending on the initial output from the feed-forward algorithm. The feedback signals will vary depending on the stability of the sample input. Second, the training of the feedback path is conducted using a set of pairs consist of two face images. The use of these pairs facilitates the adjustment of the weights in the feedback path. The training phase is complete as soon as the feed-forward and feedback paths both have been trained. It should be noted that the two different parts of the network were trained separately. Consequently, neither part influences the other during the training phase. Figure 8 shows the three age group (AG) network such as Young adults, Middle adults and Old adults.

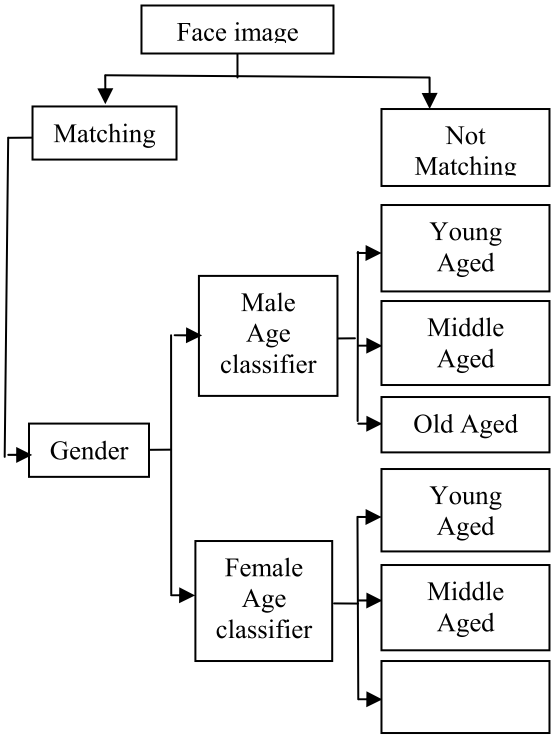


Figure 6. Complete Classifier flow for FEBFRGAC

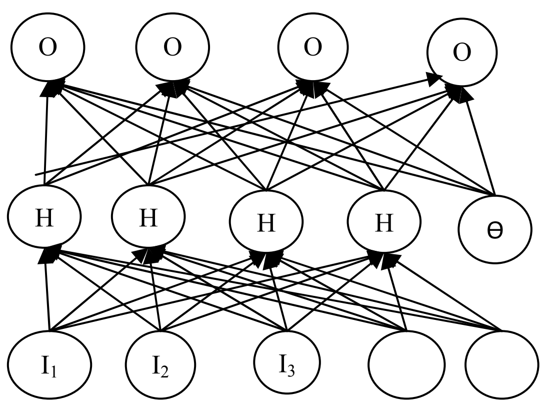


Figure 7. The structure of a back propagation network

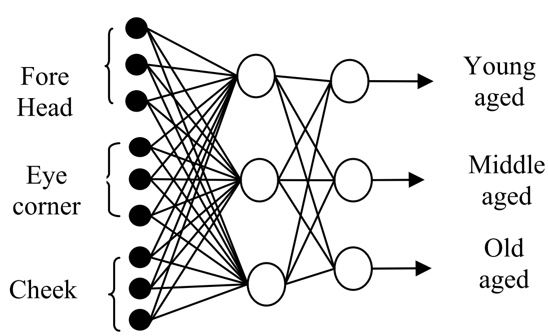


Figure 8. Age group classification network.

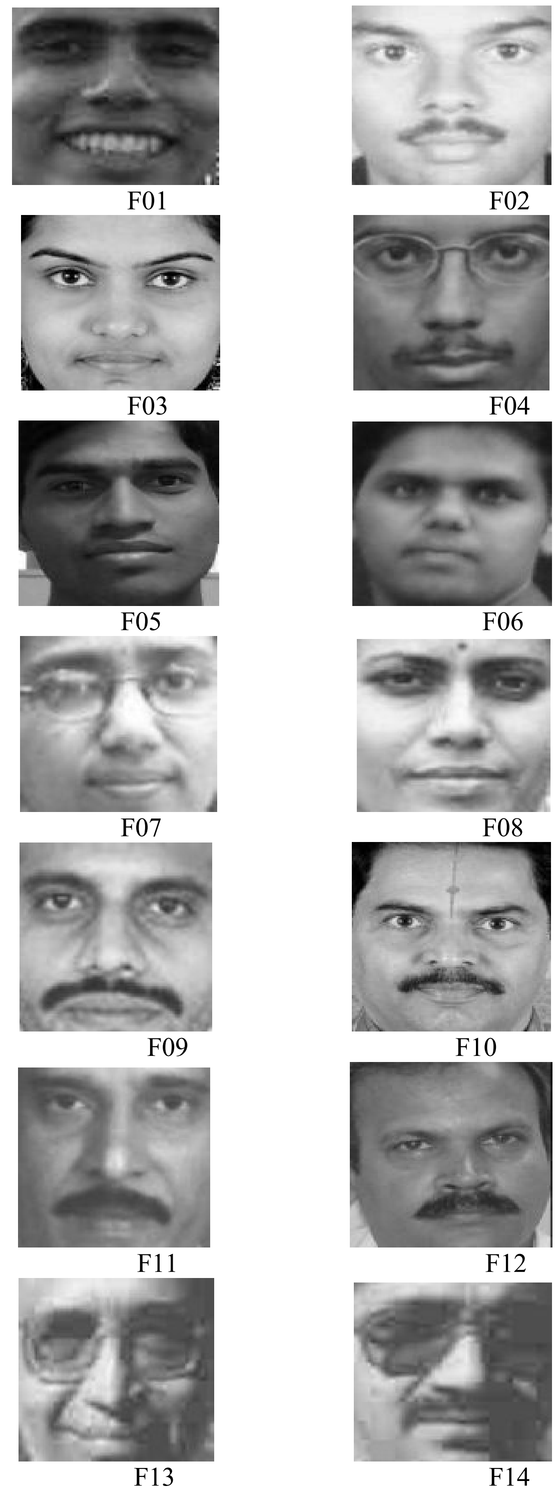


Figure 9. Facial test images.

IV. ALGORITHM: FEBFRGAC SYSTEM.

Problem definition:

Given test face image, large face image database, output verified is face image, gender and age.

TABLE I. FEBFRGAC ALGORITHM.

- Input: Test face image and face image database.
- Output: Face recognition, gender classification and age determination.

1. Pre-processing.
2. Feature extraction from the face image by using shape and texture transformation for face recognition.
3. Feature viz., total number of white pixels, mustache and left and right eye tail regions are extracted for gender classification.
4. Feature such as wrinkle are extracted for age identification.
5. Posteriori class probability and ANN classifiers are used for gender and age classification respectively.
6. Verification of test face image with the face database.

Table 1 gives FEBFRGAC algorithm to identify face and classify gender and age based on features of face image.

V. PERFORMANCE ANALYSIS

The face images of different age and gender are considered for performance analysis as shown in Figure 9. Facial features eyes, nose, chin and lip distances along with mean, variance (var) and standard deviation (S.D) are computed and tabulated in Table 3 for images F01-F14. The mean, variance, standard deviations of FEBFRGAC and ACFI (Age Classification using Facial Image) are compared in Table 2. The values of mean, variance and standard deviation using FEBFRGAC are much higher than ACFI, which gives better results for less number of facial image data base. The ratios are selected in such a way that it improves the values of mean, variance and standard deviation.

TABLE II. COMPARISONS OF FEBFRGAC WITH ACFI.

Subject	Algorithm	Ratio1	Ratio2	Ratio3	Ratio4
Mean	FEBFRGAC	1.4384	1.4384	0.6789	1.3773
	ACFI	1.3697	1.3697	0.5574	0.5602
Var	FEBFRGAC	0.0456	0.0225	0.0253	0.3142
	ACFI	0.0227	0.0032	0.0012	0.0072
S.D	FEBFRGAC	0.2135	0.1501	0.1591	0.5605
	ACFI	0.1507	0.0567	0.3475	0.0268

Gender classification based on the Probability Distribution Function method as shown in Table 4. If the total number of pixels of skin color, mustache and right_eye tail is greater than 1900 and less than 1750 pixels or total number of pixels of left_eye tail and lip_region is greater than 82 pixels then facial image is classified as male. If the total number of pixels of skin color, mustache and right_eye tail lies between 1750 and 1900 pixels or sum of left_eye tail region and lip_region pixel values lesser than 82 then classified as female. It is observed that gender recognition rate is 95%.

TABLE III. THE VALUES OF RATIOS, MEAN, VARIANCE AND STANDARD DEVIATION FOR FEBFRGAC

Subjects	Ratio1	Ratio2	Ratio3	Ratio4
F01	1.5574	0.9096	0.5841	2.5784
F02	1.3960	0.9422	0.6749	0.8498
F03	1.5089	0.9516	0.6307	1.2015
F04	1.8963	0.9068	0.4782	1.1259
F05	1.2441	0.8826	0.7093	2.3339
F06	1.6259	0.8957	0.5509	1.7094
F07	1.5828	0.9985	0.8456	0.9103
F08	1.3249	0.9938	0.7500	0.9380
F09	1.6641	0.9032	0.5427	1.0269
F10	1.2656	0.9916	0.7835	1.8577
F11	1.1734	0.9320	0.8784	1.9842
F12	1.2176	0.9494	0.7798	0.6362
F13	1.4005	0.9025	0.6444	1.2310
F14	1.2799	0.8349	0.6524	0.8986
Sum	20.1374	12.9944	9.5049	19.2818
No. of elements	14	14	14	14
Mean(avg)	1.4384	0.9282	0.6789	1.3773
Variance	0.0456	0.0225	0.0253	0.3142
Std. Deviation	0.2135	0.1501	0.1591	0.5605

TABLE IV. GENDER RECOGNITION

Gender	Sample size	Correctly Labeled(CL)	Correct Rate(CR)	Total CR
Male	40	38	95%	94.82%
Female	18	17	94.44%	

Age group classification is done using ANN method and comparison of FEBFRGAC and CAGBFF (Classification of Age Group based on Facial Features) is shown in Table 5. The accuracy of age classification is around 90% in the case of proposed algorithm FEBFRGAC compared to 79% in the case of existing algorithm CAGBFF; hence the proposed algorithm is better in classifying age groups.

Age group classification is done using ANN training method as shown in Table 6. If the total number of pixels for forehead region and the eyelid region is greater than 140 pixels and lesser than 150 pixels or the sum of forehead region and the eyelid region is lesser than 100 pixels then the facial image is classified as young aged (less than 30 years). If the product of right_canthus region and the left_canthus region pixels is more than 44000 and less than 45000 or lesser than 22000 then the facial image is classified as middle aged (30-40 years). If the number of pixels other than the above features is classified as old aged (more than 40 years).

TABLE V. AGE GROUP NETWORK.

Algorithm	AG	Sample size	CL	CR	Total CR
FEBFRGAC	Y	28	25	89.3%	89.65%
	M	20	18	90%	
	O	10	09	90%	
CAGBFF	Y	44	37	84.4%	78.49%
	M	32	25	78.1%	
	O	17	11	64.7%	

TABLE VI. RESULTS OF THE COMPLETE AGE CLASSIFICATION

Subjects	Ratio2 Threshold=0.21	No. of pixels	Computed label
F01	0.9096	140	Young
F02	0.9422	142	Young
F03	0.9516	147	Young
F04	0.9068	144	Young
F05	0.8826	146	Young
F06	0.8957	149	Young
F07	0.9985	141	Young
F08	0.9938	408	Middle
F09	0.9032	418	Middle
F10	0.9916	808	Old
F11	0.9320	826	Old
F12	0.9494	875	Old
F13	0.9025	818	Old
F14	0.8349	861	Old

The age group classification depends on the number of pixels on the face image. The subjects 1 to 7 has pixels approximately equal to 150 referred as Young aged, the subjects 8 and 9 has pixels approximately equal to 410 referred as Middle aged and the subjects 10 to 14 has pixels approximately equal to 810 referred as Old aged is as shown in the Figure 10. It is observed that as age increases number of pixels also increases correspondingly.

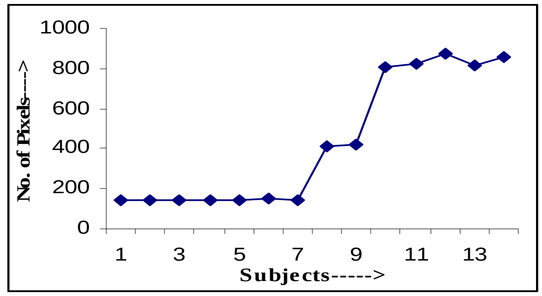


Figure 10. No. of pixels versus age group classification.

VI. CONCLUSION

Biometrics is the usage of physiological characteristics or behavioral traits for verification of an individual. In this paper FEBFRGAC algorithm is proposed. The face images are preprocessed and Canny edge detector is used to derive the edges of face images. The features of face are used for matching. The gender is classified using Posteriori class probability classifier and ANN is used to classify age, based on features of face images. It is observed that face matching ratio is 100%, gender classification is 95%, and age classification is 90%. In future the algorithm may be modified for different face angle and illumination variations.

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