ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Age Group Classification System Using Shape Features

Dr.Uppu Ravi Babu

Professor, Dept. of Computer Science and Engineering. Narsimha Reddy Engineering College, Secendrabad, TS, India

ABSTRACT: Human Age group classification can automatically done by using facial image analysis. Facial image analysis has lots of applications, such as human computer interaction (HCI), multimedia communication. However, for existing systems it is still a challenging problem to estimate the human age group effectively. An effective and efficient age group classification system is proposed in this paper. The proposed method extract the five shape features i.e. Axis of least inertia, Average bending energy, Eccentricity, Rectangularity, solidity from Center Concentrated Matrix (CCM). The FCCM is generated from each 3×3 sub image. Based on the feature set values the present paper derives a user defined algorithm for classify the facial image into one of the 5 categories i.e., Child-Aged (0-12), Young-Adult(13-25), Middle-Aged (26-40), Senior-Aged(41-60), and senior citizen (>60). The proposed method is also tested by using the Nearest Neighbour Classification algorithm. To prove the efficiency of the proposed method, the proposed method is tested on different facial image databases. The proposed method shows high rate of classification when compared with the other existing methods.

KEYWORDS: Shape features; Age Group Classification; Center Concentrated Matrix; K-NN classifier; facial image

I. INTRODUCTION

Mobile The identification, recognition and classification of human faces are widely used in various fields in which namely, Machine Learning, Computer vision, Human Computer Interaction, Artificial Intelligence, Forensic Sciences etc. there are many challenges in the estimation of the human based on the facial image of the human. The important point for age estimation is that the feature of the human face changes with respect to the time. The main changes observed on the faces are formation of white hair, formation of wrinkles in the fore-head, coagulation of the skin, development of nasal lines, formation of black spots and dark circles under the eyes, etc. The estimation of human age has many applications in the areas of identifying the criminals and missing individual, alcohol selling agencies identifying the age of the buyer, identifying the age of the person when buying cigarettes and so on.

In past few decades so many approaches are available for estimation of age of the person by using face of the person. A recent survey on automated age estimation can be found in [2]. Kwonand Lobo [3] first worked on the age classification problem. They referred to cranio-facial research, theatrical makeup, plastic surgery, and perception to find out the features that change with age. A probe gray-scale facial image can be classified into three age groups: babies, young-adults, and senior adults. The proposed algorithm is computationally expensive. Adopting the Active Appearance Model(AAM) [4] approach, Lanitis et.al. [5] devised a combined shape and intensity model to represent face images. Age is modelled as a function of the vector of the face model parameters. The aging function is defined as linear, quadratic and cubic functions. Later, they [6] reported a quantitative evaluation of the three classifiers (quadratic function, shortest distance, and artificial neural network) usinga400 images database. Gengetal. [1] proposed an aging pattern sub-space (AGES) for estimating age from appearance. In order to handle in complete data such as missing ages in the training sequence, the AGES method models a sequence of individual aging face images by learning a subspace representation. The age of a test face is determined by the projection in the subspace that can best reconstruct the face image. Fuetal. [7] Constructed a low-dimensional manifold from a set of age-separated face images and use linear and quadratic regression functions on the low dimensional feature vectors from the respective manifolds to estimate the age of a face. Adopting similarly approach, Guoetal. [8] proposed an age manifold learning scheme for extracting face aging features and designed alocally adjusted robust regress or for learning and prediction of human age. Ramanathan etal. [9] proposed a cranio facial growth model that takes into account both psychophysical evidences on how humans perceive age progression in faces and anthropometric evidences on facial growth. The proposed model is used to predict a persons appearance across age and to improve face recognition results. Yan etal. dealt with the age uncertainty by formulating a semi-definite programming problem [10] or an EM-based algorithm [11]. By boosting Local Binary

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Pattern(LBP) [12] features, Yangetal. [13] Identified a sequence of local features which when combined into a strong classifier performs the task of age classification successfully.

Most of the conventional methods for age estimation are intended for accurate estimation of the actual age. However, it is difficult to accurately estimate an actual age from a face image because facial age progression is subject-dependent. Fortunately, it is not necessary to obtain the precise estimates of the actual age for some applications. Most of the age estimation approaches adopted the regression method to predicate exact age from face image. It is difficult to predicate age by using the limited training samples with discrete age values (sparse, not continuous).

II. RELATED WORK

J SasiKiran et al., [14] Proposed Second order image compressed and fuzzy reduced grey level (SICFRG) model, which reduces the dimensionality of the image and also reduces the grey level range without any loss of important feature information. This method also classifies the facial image into 5 classes and method applied ion only 1502 sample facial images. The average efficiency of proposed method is about 96.12%.

G S N Murthy et al., [15] derived "Transition based Fuzzy LBP" (TFLBP) method for the classification of facial image into five categories such as child, young adults, middle-aged, senior age and Senior citizens. The proposed method is applied on 1602 image and got the efficiency about 96.12%. This method is also classifying the images into five categories.

V V Kumar et al., [16] proposed Topological Texture Features (TTF). Based on the TTF facial image is classified into five categories i.e., child, young adults, middle-aged, senior age and Senior citizens. The authors derived TTF's on Second Order image Compressed and Fuzzy Reduced Grey level (SICFRG) approach. The proposed method is applied on 1602 image and got the average efficiency about 96.17%.

The main objective of the proposed system is that without using any standard classification algorithms for classifying the human age group. In literature, proposed approaches are used the standard classification system for classifying the human age group so that it will take time for both extraction of the features from human facial image and also for classification system. In some proposed approaches in literature, uses user defined algorithms for classifying the human age group by using human facial image but not used the standard classification algorithm. The main objective of the proposed method is to fit for both the approaches i.e. for user defined and algorithm and also for standard classification algorithms. No such method is available up to now. If correct features are extracted then it is fit for both standard classification and also for user define algorithm. So, the present paper concentrate on this point and develops a method called Shape feature based Age group classification system for classifying the human age group of facial images.

The rest of the papers is organized as follows. In section 2, describes the proposed method and results and derived user defined algorithm are explained in section 3. Finally, conclusion are given in section 4

III. PROPOSED METHODOLOGY

In The proposed method of age group classification system can be shown by using the block diagram which is shown in figure 1. The block diagram indicates that the proposed method mainly consists of 5 steps. In the first step, considers the facial image and crop the facial gray level image. In the second step, convert the RGB facial image into Grey level image using Weighted RGB conversion method. In step 3, generate the Centre Concentrated Matrix (CCM) from grey level image. In step4, extract the shape features like Axis of least inertia, Average bending energy, Rectangularity, Solidity and add these features to feature vector. Based on the feature values in feature vector derive an algorithm for classifying the test facial image into one of the 5 categories i.e., Child-Aged (0-12), Young-Adult(13-25), Middle-Aged (26-40), Senior-Aged(41-60), and Senior-Citizen (>60) in the final step.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

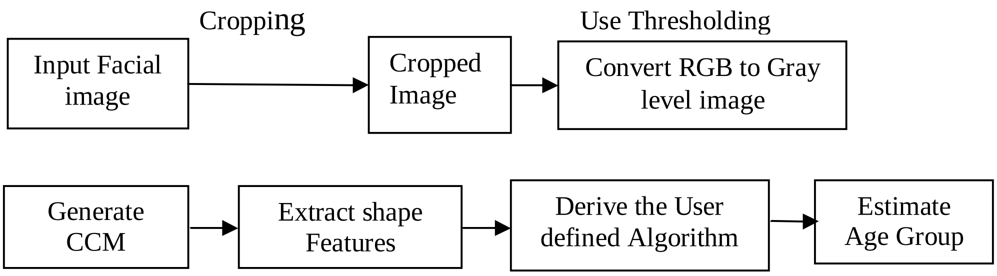

Figure 1: block diagram of the proposed Age-group Classification System

A. *Crop the facial image:*

The proposed method extract the shape features from skin region of the facial image. Cropping is necessary for eliminating the unnecessary parts of the skin region of facial image such as neck, hair and so on. It is frequently the case that the input image has more information than just the face, so the background and part of the body also appear in the image. Since we will only use facial information we need the image to be fitted to the face due to avoid this extra information than will only affect the system performance. Then convert the cropped facial image into grayscale image. The input image and resultant cropped image is shown in figure 2.

(a) (b)

Figure 2: Image Cropping of facial image. a) Original image b) cropped image

B. *Convert RGB to Gray level image:*

To extract the shape features from the facial image, first need to convert the input RGB colour image into gray level image. The proposed method utilizes the Weighted RGB conversion method. Generally, the RGB image is composed by 3 dominated colours i.e. Red (R), Green (G) and Blue (B). In Weighted RGB conversion process, different weights are assigned to each colour component and these three components are utilized for converting the colour image into grey level image the conversion process is represented by using the equation (1). The resultant image is shown in figure 3.

$$G(x,y) = 0.3 * R(x,y) + 0.59 * G(x,y) + 0.11 * B(x,y) \qquad eq.(1)$$

Where G is gray value at location (x,y) and R G B are the colour component values and x,y are the pixel positions.

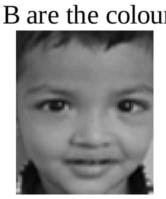

Figure 3: resultant grey level image

C. *Generate Centre Concentrated Matrix(CCM):*

To extract the feature set values from a facial image, we are going to generate the CCM. For generating the CCM the following procedure is adopted. For 3×3 window, the centre pixel value is treated as thresh hold (Th) value. Based on Th value, it's neighbouring values are changed to either zero(0) or one(1) by using the following equation 2. Repeat the same process for rest of facial image.

$$CCM(x,y) = \begin{cases} 0 \; if \; Img(x,y) < Th \\ 1 \qquad otherwise \end{cases} \quad x \; and \; y = 1,2,3 \qquad eq.(2)$$

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Where Img is the gray level image and x and y are pixel coordinators. The sample conversion of the Grey level matrix to CCM is shown in figure 4.

154	167	163
167	167	162
167	163	163

0	1	0
1	1	0
1	0	0

Figure 4: Grey to CCM conversion procedure (a) 3×3 window gray level values (b) the corresponding CCC matrix values

D. *Extract the shape features from CCM*

From the generated CCM, the shape features can be extracted. The shape features gives more information about the surface of the face. The present papers uses the shape features only because of continues changes occurs on face when age grows. These changes are identified by using shape features. The shape features used in the present approach is Axis of Least Inertia, Average Bending Energy, Eccentricity, Rectangularity, and Solidity. Based on these shape features, the age group of a person can be calculated.

IV. Results and Discussions

To test the proposed method, among numerous available face databases around the globe, four of them are considered which incorporates huge set of images. The MORPH Database is made out of 17,000 images of about 4,000 people, between 15-68 age of males and females. The second considered database is FG-NET (Face and Gesture Recognition Research Network) ageing database. FG-NET database is made out of 1002 images of more than 80 people, from the ages of 0 - 69 years and 500 images of 50 people from Google database. 600 images gathered from the scanned photos in the age range from 0 to 80. This leads a sum of 19102 example facial images. In the proposed system the test images age group estimate into five age groups of Child (0 to 12years), Young Adult (13-25), middle age group (26 to 40 years) and Senior Aged (41-60 years),senior citizen group(>60). Some of the images from different data bases are shown in figure 5. The feature set values of the each category is listed out in tables from 1 to 5. Based on these feature set values the tested image is classified by using one of the two approaches. The approach uses the standard classification algorithm and second approach uses a user defined algorithm.

Figure 5: Sample facial images of various age groups

A. *By using Standard classification Algorithm*

In this paper, for testing the proposed method, Nearest Neighbor Classifier (NNC) is used for classification purpose. All experiments are carried out on a PC machine with i3 processor 3.2 GHz CPU and 4 GB RAM memory under

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

MatLab 10.0 platform. 30 percentage of the each database is used for training and reaming 70 percentage images are used for testing purpose i.e. 5730 images are used for training purpose and 13372 images are used for testing purpose. The percentage of classification of the proposed method when NNC is applied is listed out in tables 6.

Table 1 : Feature set values for child age group extracted from CCM

Sno	Image Name	Axis of least inertia	Average bending energy	Solidity	Eccentricity	Rectangularity
1	001A02	0.03045	0.42985	34.9385	0.3199	0.298
2	001A05	0.03073	0.49085	26.9078	0.341	0.338
3	001A08	0.03054	0.5243	30.955	0.3518	0.361
4	001A10	0.03036	0.4921	34.9704	0.3406	0.339
5	002A03	0.03073	0.49615	25.8881	0.3429	0.342
6	002A04	0.03073	0.49085	26.9078	0.341	0.338
7	002A07	0.03045	0.4958	33.9506	0.342	0.342
8	008A06	0.03027	0.468	36.966	0.3323	0.323
9	009A00	0.03073	0.56185	26.9397	0.3647	0.386
10	010A01	0.03054	0.5296	29.9353	0.3536	0.364
11	gi008	0.03073	0.49085	26.9078	0.341	0.338
12	gi003	0.03045	0.42985	34.9385	0.3199	0.298
13	gi002	0.03054	0.458	30.9232	0.3297	0.316
14	gi009	0.03054	0.458	30.9232	0.3297	0.316
15	gi007	0.03064	0.46245	29.9034	0.3313	0.319
16	gi005	0.03064	0.4636	29.9034	0.3316	0.32
17	si001	0.03036	0.47125	36.9462	0.3335	0.325
18	si003	0.03073	0.49085	26.9078	0.341	0.338
19	si005	0.03036	0.40885	36.9341	0.3126	0.284
20	si009	0.03027	0.468	36.966	0.3323	0.323

Table 2: Feature set values for young age group extracted from CCM

Sno	Image Name	Axis of least inertia	Average bending energy	solidity	Eccentricity	Rectangularity
1	009A13	0.02134	0.458	40.9232	0.328	0.313
2	001A14	0.01914	0.384	42.9692	0.3019	0.263
3	002A15	0.01638	0.384	42.9692	0.3014	0.262
4	001A16	0.01996	0.46305	38.8771	0.3305	0.316
5	001A18	0.01941	0.42985	38.9385	0.3179	0.294
6	011A17	0.01969	0.44085	46.9078	0.3223	0.301
7	003A25	0.01886	0.35065	49.9801	0.2901	0.241
8	012A21	0.01914	0.384	42.9692	0.3019	0.263
9	012A23	0.01941	0.43375	43.9187	0.3193	0.296
10	gi016	0.01904	0.4297	43.989	0.317	0.293
11	gi020	0.01803	0.3186	71.0767	0.2773	0.219
12	gi013	0.01969	0.39085	46.9078	0.3057	0.268
13	gi018	0.01886	0.40885	48.0043	0.3097	0.279
14	gi020	0.01932	0.40885	37.9341	0.3106	0.28
15	gi022	0.01877	0.3977	51.0318	0.3056	0.272
16	gi025	0.0196	0.46245	39.9034	0.3293	0.315
17	gi021	0.01868	0.3846	53.0076	0.3011	0.263
18	gi012	0.0195	0.458	40.9232	0.3277	0.312
19	si015	0.01868	0.38235	54.0274	0.3002	0.262
20	si017	0.01932	0.40955	38.9341	0.3109	0.28

Table 3: Feature set values of middle age group extracted from CCM

Sno	Image Name	Axis of least inertia	Average bending energy	solidity	Eccentricity	Rectangularity
1	012A32	0.03045	0.4492	40.9385	0.3457	0.311
2	013A34	0.02972	0.3495	55.0153	0.3084	0.244
3	018A34	0.03054	0.4778	39.9232	0.3561	0.33
4	019A37	0.03018	0.4612	41.9813	0.3481	0.318
5	020A36	0.03018	0.40245	42.9692	0.3285	0.279
6	021A39	0.02981	0.3546	52.9757	0.3105	0.247
7	025A34	0.02953	0.3826	58.0427	0.3186	0.266
8	001A43a	0.03045	0.4492	38.6168	0.3457	0.311
9	005A45	0.02972	0.39945	54.0274	0.325	0.277
10	006A42	0.02972	0.39945	54.0274	0.325	0.277
11	gi026	0.02926	0.3519	66.0734	0.3068	0.245

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

12	gi028	0.03008	0.3863	45.9648	0.3225	0.268
13	gi040	0.02962	0.3796	57.501	0.3178	0.264
14	gi042	0.02953	0.3826	58.0427	0.3186	0.266
15	gi045	0.03008	0.45765	43.0011	0.3467	0.316
16	si039	0.02962	0.38475	57.0229	0.3196	0.267
17	si045	0.03027	0.4828	38.9857	0.3559	0.333
18	si038	0.02962	0.38475	57.0229	0.3196	0.267
19	si041	0.03091	0.4506	38.2644	0.3486	0.312
20	si035	0.0299	0.4176	50.0123	0.3319	0.289

Table 4: Feature set values of senior age group extracted from CCM

Sno	Image Name	Axis of least inertia	Average bending energy	solidity	Eccentricity	Rectangularity
1	003A51	0.03045	0.4999	38.9385	0.4132	0.344
2	003A57	0.03027	0.4755	38.9539	0.4047	0.382
3	003A58	0.03027	0.5236	39.9736	0.4207	0.36
4	003A59	0.0299	0.4705	50.012	0.402	0.341
5	003A60	0.0299	0.4705	50.012	0.402	0.342
6	004A53	0.0299	0.4705	50.012	0.402	0.354
7	006A54	0.03045	0.5047	38.9187	0.4149	0.347
8	006A55	0.02999	0.4349	46.9846	0.3904	0.351
9	039A50	0.02999	0.4905	45.9967	0.409	0.381
10	003A47	0.03027	0.5341	38.9857	0.4243	0.367
11	003A49	0.03045	0.5666	38.2768	0.4356	0.389
12	004A48	0.02962	0.428	57.0229	0.3772	0.392
13	gi046	0.03054	0.5986	39.9353	0.4466	0.41
14	gi048	0.02999	0.4905	45.9967	0.409	0.383
15	gi050	0.02999	0.4286	47.9725	0.3882	0.342
16	gi052	0.02972	0.4546	53.0076	0.3964	0.341
17	gi055	0.02999	0.4286	47.9725	0.3882	0.357
18	gi041	0.02972	0.4446	53.0076	0.3831	0.367
19	gi052	0.0299	0.4729	48.9922	0.4029	0.362
20	gi055	0.02981	0.4604	52.0197	0.3984	0.381

Table 5: Feature set values of senior citizen group extracted from CCM

Sno	Image Name	Axis of least inertia	Average bending energy	solidity	Eccentricity	Rectangularity
1	006A69	0.02193	0.4921	40.9704	0.3386	0.335
2	003A61	0.0216	0.4927	50.9999	0.3368	0.334
3	004A53	0.02192	0.5055	38.9539	0.3427	0.344
4	004A62	0.02185	0.5076	60.0504	0.3414	0.345
5	004A63	0.0219	0.5174	47.0164	0.3459	0.352
6	005A61	0.02197	0.5409	46.9078	0.3557	0.368
7	006A61	0.02193	0.5421	39.9704	0.3553	0.368
8	006A67	0.0256	0.5009	62.0581	0.3385	0.34
9	004A64	0.02189	0.5505	50.012	0.3567	0.374
10	004A61	0.02193	0.5162	39.2326	0.3465	0.351
11	gi066	0.03	0.4885	45.9967	0.3564	0.337
12	gi068	0.0301	0.5863	45.9648	0.3692	0.402
13	gi065	0.0299	0.5684	49.9801	0.3624	0.39
14	gi062	0.0302	0.5612	41.9813	0.3614	0.385
15	gi065	0.0305	0.5278	40.9232	0.3527	0.363
16	si070	0.0298	0.5596	51.9878	0.369	0.384
17	si068	0.0301	0.5452	43.9571	0.3558	0.374
18	si071	0.0302	0.5112	41.9813	0.3647	0.352
19	si269	0.0303	0.5722	39.9736	0.3655	0.392
20	si066	0.0292	0.485	70.5668	0.3503	0.334

Table 6: Overall percentage of classification Age Group Classification System

Age group	Classification Rate Databases				
	Morph	Fg-Net	Google	Scanned	Overall %
Child (0 to 12 Years)	96.55	95.59	96.87	96.13	96.285
Young Adult (13-25 years)	95.55	94.97	95.91	96.17	95.65
Middle aged(26 to 40 Years)	96.13	96.64	96.13	95.94	96.21

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Senior Aged (41-60 years)	97.19	96.63	96.37	95.79	96.51
senior citizen (>60 years)	93.83	95.62	96.45	95.91	95.45
Overall % in database	95.85	95.89	96.34	95.99	96.02

B. *By using User defined classification Algorithm:*

Based on the extracted feature set values, the present paper derives a user defined algorithm called Shape feature based classification algorithm. The input for the proposed algorithm is feature set values and the output of the algorithm is one of the five Age groups, the detailed Shape feature based classification algorithm is shown in Algorithm 1. The classification results proposed method when user defines algorithm is applied is listed out in table 7.

Algorithm 1: Estimation of age group of a person using Shape features

START
if Solidity is less than 37 then
    print" Test image age group is Child age (0 to 12years)"
else if Solidity is greater than 37 and Axis of least inertia is less than or equal to 0.02134 then
    print" Test image age group is Young Adult age (13 to 25 years) "
else if Rectangularity is less than or equal to 0.333 then
    print" Test image age group is middle age group (26 to 40 years) "
else if Eccentricity is less than 0.37 then
    print" Test image age group is Senior Citizen (> 60 years) "
else if Eccentricity is greater than 0.37 then
    print" Test image age group is Senior Aged group(41-60 years) "
otherwise
    print " unknown age group"
END

Table 7: Percentage of classification when User defined algorithm is applied

Age group	Classification Rate Databases				
	Morph	Fg-Net	Google	Scanned	Overal %
Child (0 to 12 Years)	96.33	95.12	96.34	96.31	96.025
Young Adult (13-25 years)	94.75	94.83	95.99	96.75	95.58
Middle aged(26 to 40 Years)	96.31	96.36	96.31	96.06	96.26
Senior Aged (41-60 years)	96.96	96.12	95.73	96.17	96.245
senior citizen (>60 years)	94.25	95.07	95.57	96.14	95.2575
Overall % in database	95.72	95.5	95.988	96.29	95.8735

From the above two approaches the NNC technique is show slightly higher rate bur when standard classification applies time complexity is more. When the user defined algorithm applies time complexity is less.

C. *Comparison Of The Proposed Method With Other Existing Methods:*

To evaluate the efficiency of the proposed method is compared with other age classification techniques [16,17] and Sneha (2012)]. The method proposed by Pullela SVVSR Kumar et.al [16] classifies facial images into four age groups based on integrating the features derived from Grey Level Co-occurrence Matrix (GLCM) with a new structural approach derived from four distinct LBP's (4-DLBP) on a 3 x 3 image. The age group classification method proposed by Sneha Thakur et.al [17] classifies facial images into five age groups is based on the supervised Neural Network with back propagation algorithm. The classification percentage of proposed method and other existing methods are listed in table 8. The graphical representation of the percentage mean classification ratefor the proposed method and other existing methods are shown in figure 6.

Table 8: Classification rate of the proposed Shape feature based method with other existing methods

Sno	Data Base	Integrated Approach	NN with back propagation algorithm.	Proposed Shape feature based method
1	FG-Net	93.23	89.25	95.69
2	Scanned Images	92.5	88.65	96.13
3	Google	91.5	90.15	96.16
4	MORPH Database	91.75	90.64	95.78

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

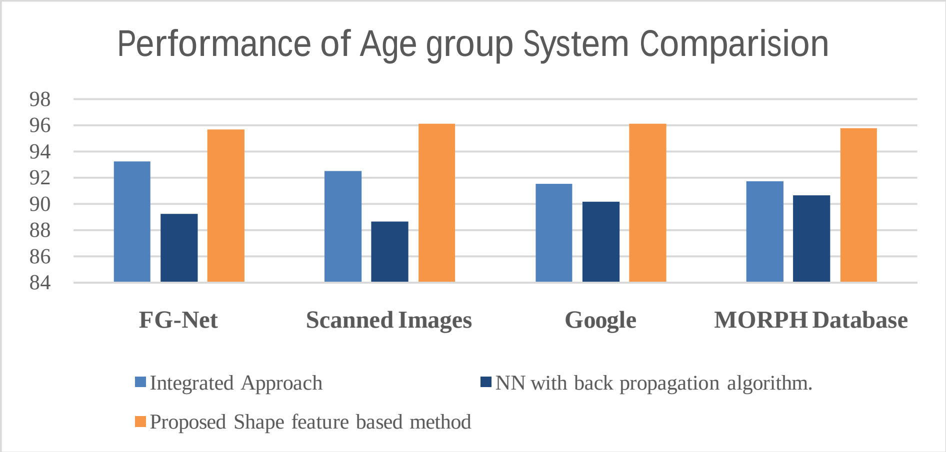

Figure 6: Comparison Chart of the Age group classification System

From the figure 6, observe that the present method shows highest percentage of classification compare to other existing methods in the literate and related work methods.

V. Conclusion and Future Work

The proposed method drastically reduced the computational time because of simple procedure is applied for each and every step of the proposed method. The proposed method is tested in two approaches. In the first approach NNC is used for classifying the human age into 5 categories. The overall efficiency of the proposed method is 96.02 when NNC applied. In the second approach derived user defined age group classification algorithm called Shape feature based classification. The overall efficiency of the proposed method in the second approach is 95.87. Innovate of the proposed method is that classification is done in two approaches. Until no such method is available to test the method in two approaches. The overall efficiency of the proposed method is 95.946. The efficiency of the proposed method is highly compared to all other methods and no method has correctly classified the human age into five categories. The proposed method exhibits high average rate of classification when compared to the existing methods.

.

References

1. X.Geng, Z.H.Zhou, Y.Zhang, G.Li,H.Dai, "Learning from facial aging patterns for automaticageestimation",in:ProceedingsofthefourteenthAnnualACM InternationalConferenceonMultimedia,,pp.307–316, 2006.
2. N.Ramanathan,R.Chellapa,S.Biswas,"Ageprogressioninhumanfaces:a survey",,J.Vis.Lang.Comput.Vol 15, pp:3349–3361, 2009.
3. Y.H.Kwon,N.D.V.Lobo,"Ageclassification fromfacialimages",in:Proceedings of the1994IEEEConferenceonComputerVisionandPatternRecognition, ,pp.762–767. 1994.
4. T.F.Cootes,G.J.Edwards,C.J.Taylor,Activeappearancemodels,IEEETrans. PatternAnal.Mach.Intell)pp: 484–498. 1998
5. A.Lanitis,C.Taylor,T.Cootes,Towardautomaticsimulationofagingeffectson face images,IEEETrans.PatternAnal.Mach.Intell.24(4, PP: 442–455, 2002.
6. A.Lanitis,C.Draganova,C.Christodoulou,"Comparingdifferentclassifiers for automaticageestimation",IEEETrans.Syst.ManCybern.vol. 34issue :1, pp:621–628. , 2004.
7. Y.Fu,T.Huang,"Humanageestimationwithregressionondiscriminativeaging manifold", IEEETrans.Multim, vol: 10, issue:4, pp:578–584, 2008.
8. G.Guo,Y.Fu,C.Dyer,T.Huang,"Imagebasedhumanageestimationby manifold learningandlocallyadjustedrobustregression",IEEETrans.Image Process, Vol:17, issue:7, pp:1178–1188, 2004.
9. N.Ramanathan,R.Chellappa,,"Modelingageprogressioninyoungfaces", in: Proceedingsofthe2006IEEEComputerSocietyConferenceonComputer Vision andPatternRecognition,vol.1.pp.387–394., 2006.
10. S.Yan,H.Wang,X.Tang,T.Huang,"Learningauto-structuredregressorfrom uncertain nonnegativelabels",in:ProceedingsoftheEleventhIEEEInternational ConferenceonComputerVision,vol 1,issue 1, pp.1–8,2007
11. S.Yan,H.Wang,T.Huang,Q.Yang,X.Tang,"Rankingwithuncertainlabels", in: Proceedingsofthe2007IEEEInternationalConferenceonMultimediaand Expo, ,pp.96–99, 2007.
12. T.Ojala,M.Pietikainen,T.Maenpaa,"Multiresolutiongray-scaleandrotation invarianttextureclassification withlocalbinarypatterns",IEEETrans.Pattern Anal. Mach.Intell., vol:24 issue:7,971–987., 2002
13. Z.Yang,H.Ai,"Demographicclassification withlocalbinarypatterns",in:S.W.Lee, S.Li(Eds.),AdvanceinBiometrics,LectureNotesinComputerScience,vol. 46 issue:2,2007,pp.464–473, 2007.
14. Jangala. SasiKiran, V. Vijaya Kumar and B. Eswara Reddy "Age Classifications Based on Second Order Image Compressed and Fuzzy Reduced Grey Level (SICFRG) Model", International Journal on Computer Science and Engineering (IJCSE), vol. 5, no. 06, pp. 481-492, Jun 2013.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

15. GortiSatyanarayanaMurty, Dr. V. Vijaya Kumar, and A. Obulesu, “Age Classification Based On Simple LBP Transitions”, International Journal on Computer Science and Engineering, vol. 5, no. 10, 2013.

16. V. V Kumar, Jangala. S Kiran and V.V. H Chandana, “ An Effective Age Classification Using Topological Features Based on Compressed and Reduced Grey Level Model of the Facial Skin”, I.J. Image, Graphics and Signal Processing(IJIGSP), vol. 6, no. 1, pp. 9-17, 2014.

17. Pullela. SVVSR Kumar, V.Vijaya Kumar and RampayVenkatarao “ Age Classification Based On Integrated Approach” , in I.J. Image, Graphics and Signal Processing, Volume 7 Pages : 50 – 57 in thear May 2014

18. Sneha Thakur et al “Age identification of Facial Images using Neural Network”, in the journal of Computer Science and Information Technologies, Volume : 3 and Issue 3 in the year 2012, Pages: 4244 – 4247.