Automatic Human Age Estimation Using Overlapped Age Groups

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Abstract. Facial aging effects can be perceived in two main forms; the first one is the growth related transformations and the second one is the textural variations. Therefore, in order to generate an efficient age classifier, both shape and texture information should be used together. In this work, we present an age estimation system that uses the fusion of geometric features (ratios of distance values between facial landmark points) and textural features (filter responses of the face image pixel values). First the probabilities of a face image belonging to each overlapping age groups are calculated by a group of classifiers. Then an interpolation based technique is used to produce the final estimated age. Many different textural features and geometric features were compared in this study. The results of the experiments show that the fusion with the geometric features increases the performance of the textural features and the highest age estimation rates are obtained using the fusion of Local Gabor Binary Patterns and Geometric features with overlapping age groups.

Keywords: Age estimation, Age classification, Geometric features, LBP, Gabor, LGBP, Cross ratio, FGNET, MORPH.

1 Introduction

Human age estimation is one of the most challenging problems in computer vision and pattern recognition. Estimating human age from his or her face is a hard problem not only for the existing computer vision systems but also for humans in some circumstances.

Aging is not a general progress, different individuals age in different ways. Aging pattern of each person is determined by many internal and external factors such as genetics, health, lifestyle, and even weather conditions [9] [10]. In order to achieve successful results in applications like age estimation or age classification, the data set that will be used to train the algorithm must contain all these factors. Therefore, the collection of training data is another difficulty of research on age progression and estimation. It is really hard to collect face images of the same person at different ages and it is highly important to assign each instance to the right age class. In order to have a

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general and qualified aging pattern that overcomes the negative influences of individual differences, a complete and accurately labeled face aging database is needed.

In spite of these present difficulties, age estimation can be used in a wide range of smart human-machine applications, e.g. limiting access to age-appropriate Internet or television contents or creating a general characteristics of a typical customer in a required age range to be used to develop a marketing strategy. Besides, facial aging is a subproblem in face recognition, because simulating the appearance of a person across years may help recognizing his or her face [17] [18].

Some earlier work has been reported on different aspects of age progression and estimation. Kwon and Lobo [14] proposed an age classification method that focuses on both the shape and the wrinkles of human face to classify input images into only one of the three age groups: babies, young adults and senior adults. Lanitis [15] presented comparative results of different classifiers; shortest distance classifier, neural network based classifier and a quadratic function classifier. The face images are represented by the AAM method and the best results were obtained when classifiers based on quadratic function and neural network based classifiers are used. Guo and Fu [11] presented a locally adjusted regressor which uses age manifold learning to map pixel intensity of the original face images into a low dimensional subspace for the learning and the prediction of the aging patterns. Yang [21] used Real AdaBoost algorithm to train a classifier by composing a sequence of Local Binary Pattern (LBP) features as a representation of face texture. Age is classified into only three periods: child, adult and old people. Gao [9] used Gabor features as face representation and the Linear Discriminant Analysis (LDA) to construct the age classifier that classifies human faces as baby, child, adult, or elder people. Images in the training set are labeled without the age information.

There exists some other work concerning face recognition with aging variations on human faces. For example, Burt and Perrett [3] described a method for the simulation of aging effects on male faces only by using facial composites which blend shape and color information. Ramanathan and Chellappa [17] proposed a craniofacial growth model that characterizes growth related shape variations observed in human faces. They used age-based facial measurements and proportion indices.

Age estimation can be considered either a classification or a regression problem [8]. We can see that for different experiment cases, the classification based age estimation can be much better or much worse than the regression based techniques. Therefore a hybrid approach which combines the classification and regression methods is the most effective solution for the age estimation problem.

Although the aging pattern is dissimilar for each person, individuals belonging to the same age group share some facial shape and texture similarities. This paper presents an extension of our previous work with a set of experiments [13]. Our original systems uses overlapping age groups (Figure 1 and Figure 2) and a classifier that measures the probability of a given image belonging to each group. Since our task is to estimate the human age, we use the interpolated probabilities to reach the final estimated age.

We formed our age groups non-uniformly to take advantage of facial feature developments of different age phases. During the formative years, facial aging effects are more pronounced, therefore we partition the formative years to smaller ranges. For the older age groups, the ranges get larger because the changes are smaller compared to

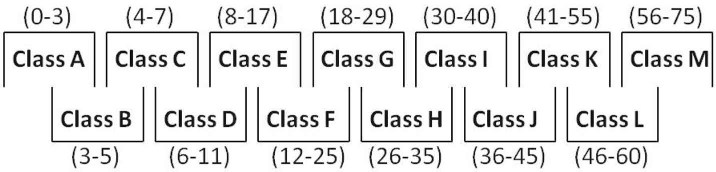


Fig. 1. The overlapping age groups for FG-NET Database [6]

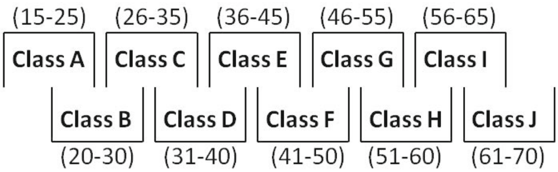


Fig. 2. The overlapping age groups for MORPH Database

the formative age groups. The age groups are chosen to overlap so that it is possible to employ an interpolation based technique to estimate the final age.

For the feature extraction process, first we calculate various ratios of the Euclidean distances between facial points to be used as geometric features. Some of these distances are calculated in a way that they are not affected by head poses and perspective distortion effects of cameras. Second, to extract textural features, we use face representation techniques such as LBP, Gabor, Local Gabor Binary Pattern (LGBP) which are commonly used by the face recognition community. Then we combine geometric and textural features and use AdaBoost algorithm to construct the final classifier. While textural features play an important role to distinguish age classes between middle age and older people, geometric features become more important to classify younger subjects.

The rest of this paper is organized as follows: Section 2 describes the proposed age estimation method. Section 3 introduces the geometric features which are used for the description of the growth related shape variations for the classification. In Section 4, textural feature extraction methods are presented. Section 5 shows comparative experimental results in age estimation for two databases (FG-NET and MORPH) and Section 6 provides some concluding remarks.

2 The Fusion of Geometric and Textural Features

Facial aging effects can be perceived in two main forms; the first one is the growth related transformations in facial shape during formative years. The other is, the textural variations such as wrinkles, creases, and other related skin artifacts that occur during adulthood. Therefore, while some earlier work deal with only facial texture to construct an age classifier [9], some use shape and texture information separately to distinguish one age class from the others [14] [21].

We tested 8 different classifiers that use different facial feature vectors. Some of these classifiers use textural features, some of them use geometric features and others

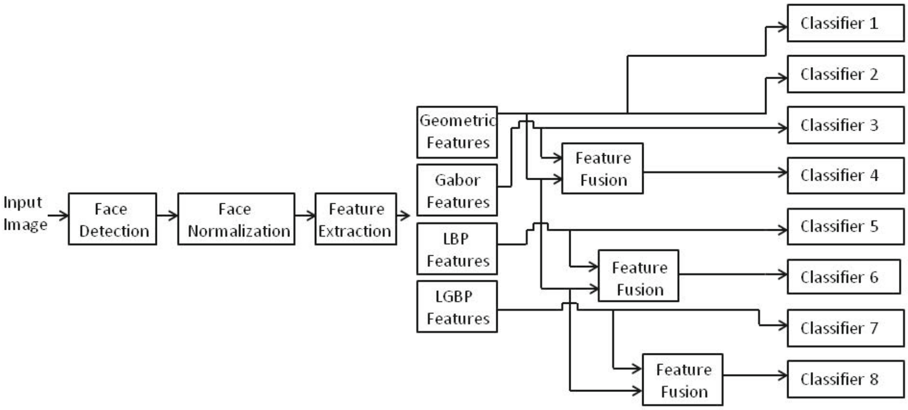


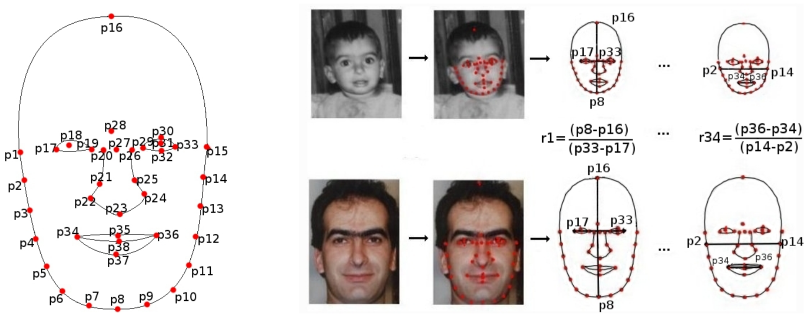
Fig. 3. The overall diagram of the proposed age classification system

use fusion of textural and geometric features. The overall feature sets of each classifier is shown in Figure 3.

Before the feature extraction phase of the training, samples in the training data set are assigned group labels. Most of the samples are assigned two group labels because our age groups overlap (Figure 1 and Figure 2). For the training, first, face boundaries are automatically detected, and face image patches are cropped from images in the training dataset. Prior to feature extraction, all images undergo geometric and illumination normalization. After the preprocessing phase, several feature extraction methods are applied to the normalized face images: 1) Ratios of the distances between facial landmarks are extracted to be used as geometric features. 2) The LBP operator is applied to every pixel of the face image and then resulting values are used as the feature vectors. 3) After convolving the face image with a range of Gabor filters, the magnitude responses are used to represent the Gabor features. 4) The LGBP representations of the face images are used as LGBP features. In addition to these extracted features, we combine each textural feature with geometric features at the feature level to enhance the representation power of the face image.

After the feature extraction phase, the AdaBoost learning algorithm [7] is used to model the age classifiers. AdaBoost algorithm combines the weak classifiers to construct a strong classifier. In every iteration, it reweighs each instance according to the output of the classifier. Finally we obtain 8 distinct classifiers; Classifier 1 uses Geometric features without cross ratio features, Classifier 2 uses Geometric features, Classifier 3 uses Gabor features, Classifier 4 uses the fusion of Geometric and Gabor features, Classifier 5 uses LBP features, Classifier 6 uses the fusion of Geometric and LBP features, Classifier 7 uses LGBP features and Classifier 8 uses the fusion of Geometric and LGBP features.

For testing, an input face image goes through the same face detection, normalization and feature extraction phases. Then, the probabilities of each age group assignment is obtained from the age group classifier. The probabilities of the highest scoring group and its two neighbors are used to calculate an interpolated age value using a weighted average of the three group centers. Age calculation function is defined as:



(a) (b)

Fig. 4. (a) 38 facial landmarks which are read from point files that are provided for face images in FG-NET Aging Database (b) Geometric Features Extraction Process

$$age = X_{med} + ((Y_{med} - X_{med})/2)P_y + ((Z_{med} - X_{med})/2)P_z \quad (1)$$

where X_{med}, Y_{med} and Z_{med} are the median age values of the age classes with the highest probabilities respectively. In the equation P_y and P_z are the second and the third highest probability values of the age classes. We found that overlapping age groups performs better with our implementation method than the non-overlapping age groups.

3 Geometric Features

Aging causes significant variations in the anatomy of human face especially during the transition period from childhood to adulthood. Changes in the shape of the face across ages can play a critical role in age estimation. In order to describe the human face geometrically, ratios of distance values between facial landmark points according to face anthropometry can be used [14]. Face anthropometry is the science of measuring size and proportions on human faces [17]. Anthropometric data have been widely used in generating geometric models of human face [4], in characterizing growth related shape variations [17] for the face recognition applications and in constructing face models for computer graphics.

In our age estimation as illustrated in Figure 4(a), we obtain 38 facial landmarks from 68 points which are read from point files that are provided for every face image in Face and Gesture Recognition Research Network (FG-NET) [6] Aging Database. In order to further test the method on the MORPH database [16], same facial landmarks are extracted automatically for each face image in the database. Then, to model the geometric shapes of human faces at different ages, we extract 34 facial proportions, ratios of distances between above mentioned facial landmarks as shown in Figure 4(b). Some of the facial proportions which are used as geometric features of the classifier are; $r_1 : (\frac{p8-p16}{p33-p17})$, $r_2 : (\frac{p8-p38}{p11-p5})$, $\ldots$, $r_{34} : (\frac{p36-p34}{p8-p27})$.

Although the geometric features of a face image are insensitive to the changes in illumination, they might be affected by head pose variations and camera distortions. In order to addres this problem, the two of the geometric features that we use in age

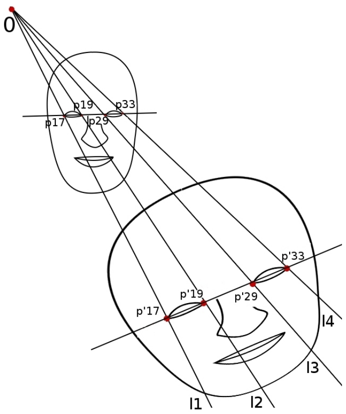


Fig. 5. Cross ratio for the eye corner points

classification are based on cross ratio of the face image. If p_1, p_2, p_3 and p_4 are four distinct points on the same line, then the cross ratio is computed as:

$$(p_1, p_2; p_3, p_4) = \frac{(p_1 - p_3)(p_2 - p_4)}{(p_2 - p_3)(p_1 - p_4)} \tag{2}$$

The cross ratio is invariant to the projective transformations. As illustrated in Figure 5, l_1, l_2, l_3 and l_4 are four coplanar lines passing through the same point O. The cross ratio of these lines is defined as the cross ratio of the intersections of these lines with any other line that does not pass through O. Therefore, the cross ratios $(p_{17}, p_{19}; p_{29}, p_{33})$ and $(p_{17}', p_{19}'; p_{29}', p_{33}')$ are equal.

In our work, we model these lines as the lines passing through the central projection of the camera and the facial points. For the first cross ratio, we use the eye corner points; $(p17, p19; p29, p33)$ (Figure 5). For the second cross ratio, we use the head point, center point of eye brows, mouth mid point and chin point; $(p16, p28; p38, p8)$. These two geometric features make our classification system robust against the perspective distortions, because the cross ratio between four colinear points stays constant under perspective transformations.

4 Textural Features

Facial aging effects, especially in older age groups, are mostly perceived in the form of textural variations such as wrinkles, creases, and changes in skin tone. Textural changes in human face provide fundamental information for the estimation of human age. Thus, the effectiveness of the textural face representation method is highly important for age estimation. In face recognition applications, the LBP operator and Gabor filters are among the most popular techniques for face representation [1] [5] [2] [19]. We use LBP, Gabor and LGBP features as textural features in age estimation as explained below.

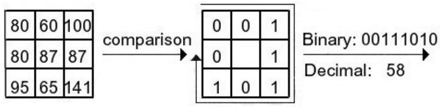


Fig. 6. The original LBP operator

4.1 LBP Features

Local Binary Pattern is a non-parametric kernel which summarizes the local spatial structure of an image [1]. The original LBP operator labels the pixel of the image by comparing it with the surrounding pixels in its $3\times$ 3-neighbourhood as illustrated in Figure 6.

The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows [1]:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{3}$$

where i_c corresponds to the gray value of the center pixel (x_c, y_c), i_n to the gray value of the 8 surrounding pixels, and function $s(x)$ is defined as:

$$s(x) = \begin{cases} 1 \; if x \geq 0 \\ 0 \; if x < 0 \end{cases} \tag{4}$$

Local binary pattern based face recognition has been proposed as a robust face recognition algorithm [1] [5]. Therefore, we use the LBP values of the pixels rather than the raw intensities as the feature vector for the classifier.

4.2 Gabor Features

Gabor filters are one of the most effective texture representation techniques for analyzing an image into a detailed local description. Gabor features are commonly used in face representation for the face recognition applications due to their robustness to image variations [2] [19].

The Gabor representation of a face image is generated by convolving it with the Gabor filters [2]. Applying a Gabor filter $\Psi_{f,\Theta}(x, y)$ to the pixel at the (x, y) pixel position in the image can be defined as:

$$g_{f,\Theta}(x, y) = f(x, y) * \Psi_{f,\Theta}(x, y) \tag{5}$$

where $f(x, y)$ corresponds to the intensity value of the pixel, f and Θ are used for controlling the scale and the orientation of the Gabor filters, respectively, and $*$ is referred as the convolution operator.

When convolving a face image with a range of Gabor filters at different orientations and scales, we can get a set of filter responses that characterize the local texture of the face image. In our method, we use 12 Gabor filters with the following parameters: $f \in \{1, 1.5, 2\}$ and $\Theta \in \{\frac{\pi}{8}, \frac{2\pi}{8}, \frac{4\pi}{8}, \frac{6\pi}{8}\}$. After convolving the face image with the Gabor filters, we obtain 12 Gabor magnitude images with 3 distinct scales and 4 distinct orientations as shown in Figure 7.

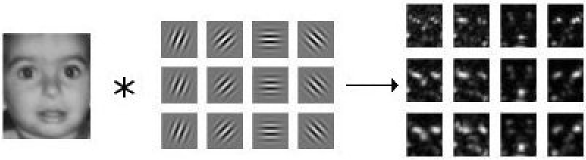


Fig. 7. Convolution of the face image with the Gabor filters

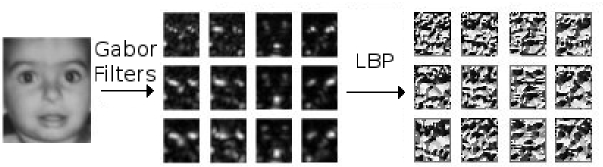


Fig. 8. LGBP face representation process

4.3 LGBP Features

Local Gabor Binary Pattern which is the combination of Gabor filters and the LBP operator, is used to enhance the information in the Gabor magnitude image. LGBP representation combines the local intensity distribution with the spatial information [22]. In order to generate the LGBP representation of a face image; the face image is convolved with multi-scale and multi-orientation Gabor filters first. Then, the LBP operator is applied to each pixel of the Gabor magnitude images as illustrated in Figure 8.

In order to obtain the LGBP representation of face images, the LBP operator is applied to each pixel of each 12 Gabor magnitude images. Then, we use the pixel values of 12 LGBP representations as LGBP features of the face image.

5 Experimental Results

We performed age classification experiments on the FG-NET Aging Database [6] and MORPH Database [16] which are the most popular databases in the face age estimation research community. The FG-NET Aging database contains 1002 high-resolution color or grayscale face images from 82 subjects ranging from age 0 to 69. Images in the database display facial appearance changes in pose, illumination, expression, etc. Also there are only few images of persons older than 40 in the database. Table 1 shows the age range distribution of the images that are used in the FG-NET experiment. The MORPH Database contains more than 55000 images of more than 13000 individuals ranging from age 16 to 77. The average number of images per individuals is 4. For MORPH experiment, we use 20 randomly selected samples for each age value which range from age 16 to 65.

In FG-NET experiment, for each sample in dataset, the age class values are labeled according to the exact age information. We used the age class scheme which is illustrated in Figure 1. Then for each classifier, Leave-One-Person-Out (LOPO) evaluation scheme is used. In each fold, all samples of a single person are used as the testing set

Table 1. The age range distribution of the images in the FG-NET Database

Age Classes	Number of Samples
(0-3)	141
(3-5)	120
(4-7)	156
(6-11)	201
(8-17)	321
(12-25)	361
(18-29)	210
(26-35)	100
(30-40)	88
(36-45)	55
(41-55)	49
(46-60)	27
(56-75)	9

Table 2. MAE of age estimation on FG-NET Database

Age Estimation Method	MAE
Classifier1 (Geometric-no cross ratio)	7.86
Classifier2 (Geometric)	6.68
Classifier3 (Gabor)	10.24
Classifier4 (Geometric+Gabor)	9.35
Classifier5 (LBP)	8.94
Classifier6 (Geometric+LBP)	8.18
Classifier7 (LGBP)	9.55
Classifier8 (Geometric+LGBP)	5.05

and the remaining samples are used as the training set. For comparison purposes, we used the Mean Absolute Error (MAE) [15] which is the most commonly used metric for age estimation. Table 2 shows the MAE of age estimation for different kinds of features which are used as face image feature vectors for the age classifiers.

It can be observed in Table 2 that, using all textural features in combination with the geometric features, contributes positively to the performance of age estimation. The combination of LGBP and Geometric features achieves 5.05 MAE on the FG-NET Aging Database. Note also that, cross ratio is a very important feature, because it improves the overall geometric estimation results.

As previously mentioned, the images in the FG-NET Database, are not equally distributed over age ranges. For a detailed analysis of the age estimation method, we calculated the MAE for each decade seperately. The comparative results of the MAEs per decade (MAE/D) for different kinds of features are shown in Table 3.

As we previously mentioned, overlapping age groups performs better with our interpolation method than the non-overlapping age groups. In order to verify this, we also tested our method with non-overlapping age class scheme. The age is partitioned into seven different classes such that ClassA (0-3), ClassB (4-7), ClassC (8-17), ClassD (18-29), ClassE (30-40), ClassF (41-55), ClassG (56-70), ClassH (70+). The samples are

Table 3. MAE/D of age estimation on FG-NET Database

Age Ranges	Feature Set							
	Geometric	LBP	Gabor	LGBP	Geo+LBP	Geo+Gabor	Geo+LGBP	Geo+LGBP (no overlap)
(0-10)	4.35	6.8	8.62	8.24	5.46	6.17	3.34	5.16
(11-20)	4.72	5.32	7.53	7.4	6.13	7.95	3.28	6.1
(21-30)	8.87	9.71	9.31	6.13	11.87	13.37	7.17	7.67
(31-40)	13.18	18.48	20.21	19.45	12.71	13.46	10.25	16.75
(41-50)	16.08	25.38	22.76	22.51	18.91	20.97	13.4	16.3
(51-60)	24.83	38.7	30.45	27.82	28.58	26.13	14.57	30.99
(61-70)	31.85	37.6	36.9	45.23	38.52	34.9	24.81	34.1

Table 4. MAE of age estimation on MORPH Database

Age Estimation Method	MAE
Classifier2 (Geometric)	15.15
Classifier3 (Gabor)	9.73
Classifier4 (Geometric+Gabor)	8.11
Classifier5 (LBP)	12.33
Classifier6 (Geometric+LBP)	10.93
Classifier7 (LGBP)	8.58
Classifier8 (Geometric+LGBP)	6.28

assigned one group label. Our best MAE for non-overlapping age groups was obtained using the fusion of LGBP and Geometric features as expected. The experimental results are shown in the last column of Table 3. The comparative results reveal that overlapping age groups performs remarkably better than the non-overlapping age groups.

The age class scheme which is used in FG-NET experiment is not adequate for MORPH experiment, because the face image dataset that is used in MORPH experiment does not contain samples for age values which range from 0 to 15. Therefore in MORPH experiment, for age class labeling process, we used another age class scheme which is illustrated in Figure 2. Then for each classifier, Leave-One-Out evaluation scheme is used. In each fold, one sample is used as the testing set and the remaining samples are used as the training set. Table 4 shows the MAE of age estimation on MORPH Database. As can be observed from Table 4, the combination of LGBP and Geometric features achieves 6.28 MAE on MORPH Database.

For a detailed analysis of the age estimation method, we calculated the MAE for each decade seperately for the MORPH Database. The comparative results of the MAEs per decade (MAE/D) for different kinds of features are shown in Table 5.

We can say that, the effectiveness of the fusion of LGBP and Geometric features result from many aspects. These include the LBP descriptor that captures small texture details, multi-scale and multi-orientation Gabor features that encode facial texture over a range of coarser scales. Finally, geometric proportions that are used for the characterization of the variations in facial shape contribute positively to the age estimation.

Table 5. MAE/D of age estimation on MORPH Database

Age Ranges	Feature Set						
	Geometric	LBP	Gabor	LGBP	Geo+LBP	Geo+Gabor	Geo+LGBP
(10-20)	21.37	16.66	13.96	9.29	13.8	11.62	9.13
(21-30)	14.65	13.76	9.19	8.33	11.69	8.04	6.5
(31-40)	11.42	8.2	9.27	7.36	8.02	7.57	5.34
(41-50)	12.49	12.03	10.7	7.97	11.11	8.38	7.06
(51-60)	16.26	12.31	7.15	9.62	10.77	6.44	5.23
(61-70)	20.5	14.13	10.78	10.03	12.32	8.57	5.43

Facial aging causes the most noticable variations in one's appearance during the formative years. As a result, the estimated age of a young person is more accurate than the older persons. As can be observed from Table 3, the MAE of age estimation at young ages is lower than the MAE of age estimation at old ages. Besides, in FG-NET experiment, there are only few old person images are used which are not enough for creating a general age estimation model. In MORPH experiment, we used same number of images for each age value and we get similar MAE values for each decade.

In this paper, we also tested the age estimation system according to the ethnicity of the subjects. For this purpose, we generated 4 different subsets of the MORPH database: Subset1(250 Black people images), Subset2(250 White people images), Subset3(250 Black people images), Subset4(250 White people images) and Subset5(Subset1+ Subset2). In these experiments Subset1, Subset2 and Subset5 were used as training sets, Subset3 and Subset4 were used as testing sets. All the face images in the subsets belong to different individuals and each subset contains equal number of samples for each gender. The experiments for different test scenarios are performed just for the fusion of LGBP and Geometric features, which was found to be the best combination by our previous experiments. Analyzing the results illustrated in Table 6, it can be observed that when the test images and the training imagesare of different races, MAE of the age estimation increases. Also when we compared the results with the Table 4, MAE of age estimation increases from 6.28 to 7.15 for black people and 7.95 for white people. In Table 4, number of training samples that were used for the experiments are 999, on the other hand it is 500 in Table 6. Therefore, this could be the reason that the MAE in Table 4 is lower than MAE in Table 6.

We also compared our results with the state of the art methods that follow the same popular Leave-One-Person-Out (LOPO) test strategy. As shown in Table 7, our method performs comparably with the state of the art approaches on age estimation.

Table 6. MAE of Different Test Scenarios on MORPH Database According to race information

Test Scenarios(Train/Test)	MAE
Subset5/Subset3 (Black+White/Black)	7.15
Subset5/Subset4 (Black+White/White)	7.95
Subset1/Subset3 (Black/Black)	6.19
Subset1/Subset4 (Black/White)	11.42
Subset2/Subset3 (White/Black)	8.96
Subset2/Subset4 (White/White)	6.62

Table 7. MAE of Different Methods on FG-NET Database

Method	MAE
Geng et al.[10]	6.77
Geng et al.[10]	8.06
Guo et al.[11]	5.07
Yan et al.[20]	4.95
Guo et al.[12]	4.77
Our Method	5.05

6 Conclusions

We presented an age estimation method that combines the geometric and textural features of human face. We propose to use overlapping age groups and a classifier to assign probabilities of a face image belonging to each group. The interpolation of the classifier probabilities produces the final estimated age. This method has the advantage of using robust classifiers in the process of numerical age estimation.

Our age group classifiers employ textural features, geometric features, and fusion of these features. Comparative experiments for different features show that for each textural feature, the fusion with the geometric features provides significant improvements. In this paper, we used the combination of geometric features and one textural feature set (LBP, Gabor, LGBP). The fusion of more than two feature sets might achieve better results. Employment of the cross ratio technique in geometric features improved the classification rates considerably. When we use the combination of LGBP and Geometric features in the AdaBoost algorithm, we obtain 5.05 and 6.28 MAE of age estimation for FG-NET and MORPH Databases, respectively. We formed different age class schemes for different datasets by using a heuristic approach. Our future work will concentrate on generating age class scheme automatically according to the characteristics of the dataset that is used in the age estimation experiments. As mentioned before, age estimation is a challenging problem even for human. Therefore we will compare performance our system with the human ability in age estimation as a future work.

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