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Age Identification System Based on Bivariate Gaussian Mixture Model

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Abstract

Age identification has a major role in particular in the areas of biometrics. Automatic age recognition tools are therefore necessary for providing effective analysis of the facial images and thereby help in the proper identification of age. This article highlights the concepts of age identification by using a mixture model based on Bivariate Gaussian Mixture Model (BGMM). In this approach the wrinkles, facial features and the eye regions are considered together with feature extraction in order to identify the individual's age group.

Keywords: Mixture model, Fusion, Wrinkles, Biometrics, Feature extraction.

INTRODUCTION

Biometrics is a specialized area of forensics which helps to identify an individual based on the traits. Most of the biometrics are utilized for the purpose of security ranging from household security, personal security, financial security etc. Among these several biometrics that are utilized for security, facial recognition, iris, figure print, voice, vain patterns [1, 2, 3] are mostly considered in cases of identification of a mishap. In all these models the biometric traits, call the features are mostly utilized for the identification of a person [4, 5, 6]. In spite of these biometrics, the identification of the criminals in committing a crime is still becoming a challenging task. With the advents in science and technology lot of technological updates are being promoted which in other words help the law breakers to utilize various sources of escape mechanisms. As the crime events are increasing drastically at an exponential speed, efforts to safe guard this crime rate is also equally necessary. Techniques like face masking's, surgeries to temper the face, age progression, obsequy the faces make the law keepers no scope to identify the law breakers. Therefore, effective mechanisms are still to be developed to combat the criminal activities. Among these activities identification of a crime face/ criminal with change in age is considered as the focal point in this article. Age progression is an inevitable process that changes the outlook of the person [7]. Many methodologies are available to identify the change in age basing on skin texture, facial structure, skin color, wrinkles, bags under the eyes etc [8, 9]. Therefore, in order to identify a criminal or a missing person based on the facial features is highlighted in this article. The main consideration in this article is to identify the present age of a person in spite of several makeups. Lot of literature has been driven in this area, however most of these works couldn't able to identify the present age group of a person more accurately because of the several factors that are associated, and mostly all the available methodologies that exists for the age estimation are based on solitary features only. Hence in this article an attempt is made to identify the current age group of the person based on the BGMM. The advantage of parametric modeling i.e. BGMM is that it can handle the varying pattern of the faces more aptly. The rest of the paper is presented as follows. In related work of the paper has recent review of the literature in this area is highlighted. Next section of the paper deals with proposed methodology based on BGMM. Then presents the considered dataset and the feature extraction is followed. Methodology and the experimentation together with the results are presented in the paper respectively. Finally, conclusion summarizes the paper.

RELATED WORK

Lot of literature is driven in this area of the age estimation. Among these methodologies, various authors were presented models based on Local Binary Pattern (LBP), Gabor filters, local face quantization together with Support Vector Machine (SVM) Jhony K. Pontes et al [10]. Models on deep learning were also considered in order to label the ages where deep convolution networks are considered for the age related feature extraction. The proposed algorithm has shown significant improvements over the previous existing models Yuan Dong et al [11]. Hayashi et al have presented a paper in which the wrinkles pattern is considered for the age estimation. However, the main disadvantage is that these estimations couldn't give proper results. G.Guo et al [12], Y.Fu et al [13], Kwon et al [14] have presented model based on regression lines to estimate the ages. Model based on hyper planning, hierarchical framework, manifold learning methods, reduction Support Vector regression (SVR) [15] are also highlighted in the literature. However, age estimation is coupled with some privileged attributes such as smoothness, wrinkles, pimples, bags under eyes which indicate the age progression [16]. Since estimation of the age with these bundled features is difficult task, hence in this paper we present a model based on parametric approaches i.e. based on BGMM, presented in section 3 of the paper. The main advantage beyond the consideration of BGMM is also highlighted helps to overcome the correlated factors associated with age progression such as skin texture etc.

Bivariate Gaussian Mixture Model (BGMM)

In this paper the Bivariate Gaussian mixture model is utilized for effective classification of ages from the facial images. Bivariate Gaussian mixture model helps in effective recognition of facial images, in particular. The main advantage behind the consideration of Bivariate Gaussian mixture model is that it can cater the facial images with wide range of features and intensity variations. Among the various other models available in the literature the Bivariate Gaussian mixture model is mainly referred due to its ability to interpret the data having both less tailed and more tailed distributions. The probability density function of Bivariate Gaussian mixture model is given by

$$f(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\left(\sqrt{1-p^2}\right)}\, e^{-\left[\frac{1}{2(1-\rho^2)}\left[\left(\frac{x-\mu_1}{\sigma_1}\right)^2 - 2\rho\left(\frac{x-\mu_1}{\sigma_1}\right)\left(\frac{y-\mu_2}{\sigma_2}\right)+\left(\frac{y-\mu_2}{\sigma_2}\right)^2\right]\right]}$$

Where μ_1 and μ_2 denotes any real numbers.

$\sigma_1>0$, $\sigma_2>0$; $-1\leq \rho \leq 1$

Where μ_1, σ_1 are the mean and variance of the image with 1st features and μ_2,σ_2 are the mean and variance of the image with the 2nd features, ρ is called the shape parameter.

Dataset Considered

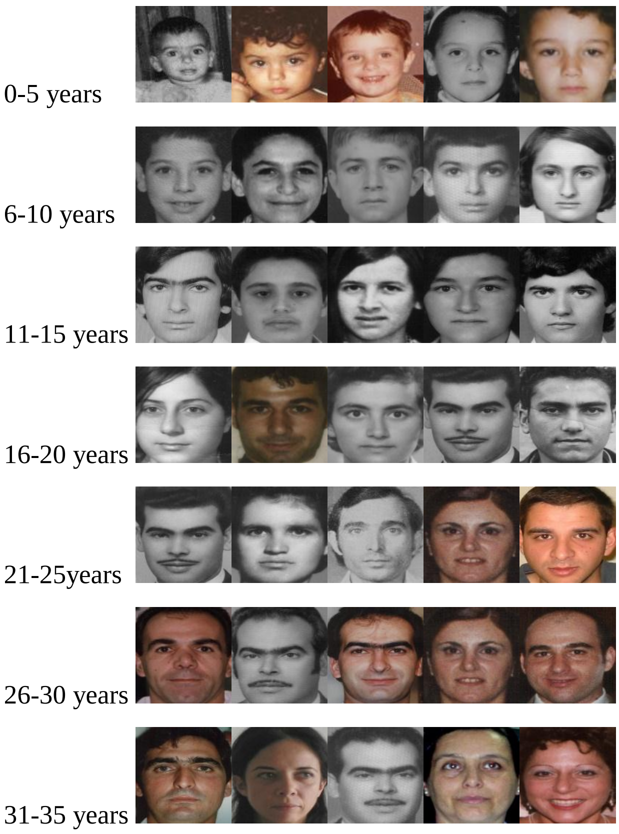
In order to present the proposed model a dataset of facial images is considered from the standard facial repository, The Face and Gesture Recognition Network (FG-NET). This dataset consists of 1002 images from 82 individuals. At the most each image occurs in the data base 12 times. The age group in the data set ranges from 0 to 69 years and for the experimentation purpose we have considered the facial images of the age groups from 5 to 50. For the testing purpose we have considered 50 images and for training purpose we considered 10 images. The database also provided with the 68 landmark points which were identified manually for all the face images that are present. Apart from the above information the database also provides information about age, gender, image size, horizontal and vertical pose, beard, hat, spectacles and mustache.

Hence the database is more suitable for research works working under age estimation, age invariant face recognition and age progression. The factors that are influenced researchers to use FG-NET are:

i) Age estimation method based on machine learning is accurate than the humans. Therefore, for machine learning approaches the database is widely used.

ii) Face recognition is one of the research area that is widely happening from 1990's. Here age invariant facial features given by database is used for better results.

iii) Similar to the above two factors age progression is also plays important role for authentication purposes which is performed by forensic artists using anthropometric studies. When it comes to automated age progression database is more useful because system derives age progression based on training data.



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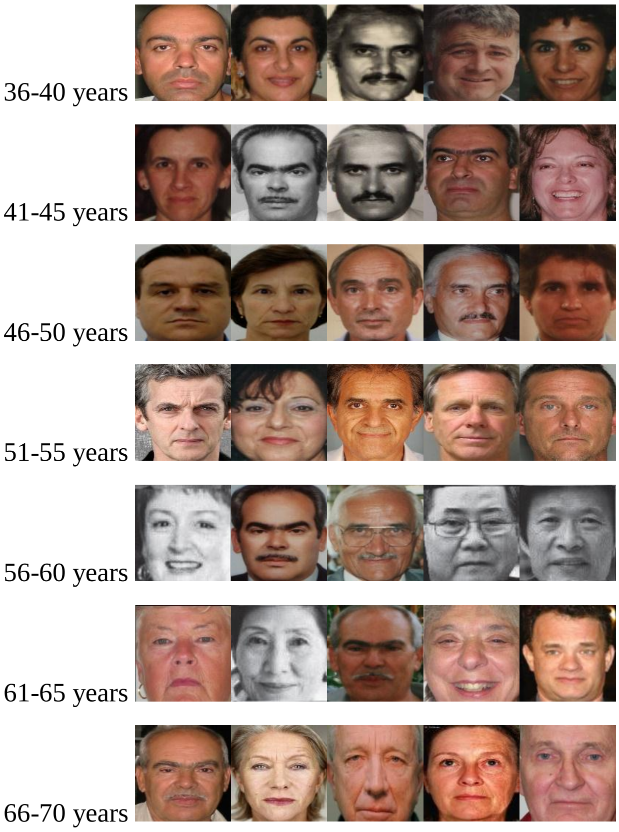

Figure 1: Sample images from the FG-NET aging database: Each row shows labeled age groups of different subjects.

Feature Extraction

In order to have the effective human age identification, two methodologies are to be considered.

1. Automatic prediction of the age
2. Prediction of age progression

The other factors that should be taken into consideration include division of facial images into categories such as infant, young adult and aged. Therefore, clustering methodologies are to be first considered to cluster the available facial data into these three groups. In order to classify the faces into each of these groups, the facial points are to be taken into consideration.
The facial points that are considered here include the distance between two eye balls and the wrinkles.

The distance between the two eye balls is calculated by the formula

$$D = \sqrt{(x_r - x_l)^2 + (y_r - y_l)^2}$$

Where x_r and y_r denote the right eye coordinates, x_l and y_l denote the left eye coordinates.

In order to identify the faces more accurately the distance between the face objects like distance between left eye and right eye, nose, chin, lip and fore head play a vital role. Therefore, these distances are to be identified first using the formula

Feature 1: (left to right eye ball distance)/ (eye to nose distance)

Feature 2: (left to right eye ball distance)/ (eye to lip distance)

Feature 3: (left to right eye ball distance)/ (eye to chin distance)

Feature 4: (eye to nose distance)/ (eye to lip distance)

Feature 5: (eye to nose distance)/ (eye to chin distance)

Feature 6: (eye to chin)/ (virtual top of head to chin distance)

Along with these features to have an effective identification of the age we have also considered wrinkles as another features. The wrinkles that are considered in this article included that of the patterns at the forehead and at the eyes. The range of these wrinkles at both the cases is considered.

METHODOLOGY

In order to present the proposed methodology, each of the images from the dataset considered are pre-processed and each of the images are normalized. Only the frontal faces are considered. From each of the faces, the distance between the eye ball and the other distances as specified in section 5 are extracted. These features are given as input's to the model presented in section 3 of the paper. Against each of the facial images in the image dataset, for each age group the ranges of the PDF'S are identified, and the dataset is divided into groups basing on the ranges. Every new face is given as input and corresponding BGMM vectors are identified as per the procedure narrated above. Then features of the query face against the range of faces in the dataset are mapped to identify the nearest matching group.

EXPERIMENTATION AND RESULTS

In order to present the proposed model, experimentation was conducted in matlab environment. Each of the images is categorized into groups based on the distance metrics and based on the wrinkles. Each facial image is considered and the facial features are extracted. These facial features are given as input to the model based on Bivariate Gaussian Mixture Model.

The wrinkles from the faces are also considered and these features are also given as inputs to the model. Using the concept of fusion these probabilities are fused. During the testing process we have considered the same procedure and the outputs obtained are presented in the following table.

Table 1: Comparison of Estimated age with Actual age of different subjects from FG-NET Dataset.

Image Number	Estimated Age	Actual Age	Differ--ence	Facial Image
001A05	6	5	1	
002A07	7	7	0	
008A12	10	12	2	
009A18	17	18	1	
012A24	24	24	0	
017A29	29	29	0	
021A35	35	35	0	
025A39	39	39	0	
028A41	41	41	0	
028A46	47	46	1	
039A52	52	52	0	
003A58	58	58	0	
004A62	62	62	0	
006A69	70	69	1	

CONCLUSION

In this paper a novel age estimation model is presented based on BGMM. In this methodology it can be easily seen that the output's derived are helping to identify the relevant are groups more robustly. The performance of the existing model is also tested with other models like Support Vector Machine (SVM), Support Vector Decomposition Machine (SVDM) and the present model is giving an overall age estimation accuracy of about 95%. This method can be extensively used in crime investigations to solve the most delayed cases during the identification of criminals.

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