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Automatic Age Estimation Based on LBP and GLCM using BGMM

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ABSTRACT

In this article a methodology is proposed for automatic age classification based on Bivariate Gaussian Mixture Model (BGMM). In the methodology the features are extracted using LBP and GLCM. These features are given as input's to the model for the classification of age groups. The experimentation is carried out using FG-NET dataset and the results are compared based on the classification accuracy. The proposed methodology exhibited the classification accuracy above 93%.

KEYWORDS: BGMM, LBP, GLCM, classification accuracy, age classification.

1.INTRODUCTION

Age classification is one of the fine consideration in some of the areas pertaining to internet access. Age classification is a fundamental problem in soft-computing, where it is necessary to estimate the age features basing on the bio-metric patterns available in particular during the criminal identification of phases. Age classification can be considered as a multifold problem where it helps in recognizing the age classification or age estimation. Age estimation generally is considered as a regression problem. Among the various associated problems of the identification of age from a biometric trait, we come across two phases, gender independent and gender dependent classification. In this article we confined ourselves to gender independent classification. Many works are presented on automatic age estimation and mostly these works are either based on age estimation, gender estimation or elasticity from the given facial templates. This classification is useful across several domains such as security, law enforcement, social media, human-computer interaction and in some particular cases of advertisements.

In most of the situations, the studies related to age estimation and classification are carried out in a controlled environment where enough care is taken during the acquisition of the faces. As the age progresses several changes attribute to the individual and these attributes play a dominating role in the process of recognition. These factors include the changing texture, color, wrinkles, dark spots, etc.

Many others have presented exemplary research for the age classification. Among these works, in some of the works, the authors have considered the combined features of the whole data set into consideration instead of considering the features of individual faces [1][2]. Works were also reported based on the general classification using gabor features for the estimation of the ages and the gender [3][4]. [5][6] have considered the ordinal features of the facial points and utilized these points for the estimation of the ages.

[7][8][9] [10] have considered the LBP variance of features for the age estimations. However, because of the varying features of the faces with respect to time, most of the above said methods are not able to estimate/classify the ages more appropriately. In order to have a proper estimation of ages, one needs to consider more than one feature into consideration. With this view point, in the present proposed work, we have considered the bivariate features based on the LBP coefficient and GLCM (Gray Level Co-Occurrence Matrix) into consideration. LBP helps to identify the invariant texture measure and GLCM helps to estimate

the features from the images more aptly. Compared to non-parametric approaches, Parametric model helps to classify the features more accurately [S.K. Pal, N.R. Pal (1993)], [Srinivas et al (2009), (2007), (2014)]. Hence in this article an attempt is made to classify the ages based on Bivariate Gaussian Mixture model together with LBP and GLCM features. The rest of the paper is organized as follows. In section 2 of the paper, the Bivariate Gaussian Mixture Model is presented. The LBP feature extraction is highlighted in section 3 and extracting the feature using GLCM is presented in section 4. Section 5 of the paper highlights about the dataset considered i.e. FG-NET. In section 6 the methodology together with experimentation is presented. In section 7 the results derived are summarized with conclusion in section 8.

2. BIVARIATE GAUSSIAN MIXTURE MODEL

Bivariate Gaussian Mixture Model (BGMM) is used for learning unsupervised data which normally distributed sub populations in an overall population. These mixture models don't require the information which population of a data point belongs to in general. BGMM have been used regularly in object tracking of different objects, hence the location of object is predicted by number of mixture components. These features formulate a basis for the consideration of the Bivariate Model. The probability density function of BGMM is given by

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

Where μ_1 and $\mu_2$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.

3. LOCAL BINARY PATTERN

Local Binary Pattern is used for classification in computer vision. In particular case of the texture spectrum model proposed in 1990 [] []. For texture classification LBP is widely used and in combination with Histogram of oriented Gradient (HOG) gives improved performance.

The formulation of LBP feature vector is described below

- The desired window was divided into cells and in general number of rows and columns of these cells should be equal.
- 8- neighbors of each pixel in a cell is compared and followed in clockwise or counter clockwise.
- Assuming the center pixel as X, hence if x is greater than neighbor's pixel value state it as 0 else 1 which cause 8-digit binary number.
- The obtained 8-digit binary number is converted to decimal for benefit.
- Normalizing the histogram obtained by computing over a cell produces the frequency of each number occurring.
- Hence feature vector for the window is obtained by concatenating histograms of all cells.

The inference of the LBP is follows

$$T = T(q_c, q_0, \dots\dots\dots\dots\dots.., q_{p-1}) \quad (2)$$

Where q_c grey value of the center pixel x and q_0 to q_{p-1} corresponds to the P number of neighbor's grey value.

The coordinates of neighbor pixels are given by

$$[X_a, Y_a] = [X_C + R\cos\left(\frac{2\pi}{p}\right), Y_c + R\sin\left(\frac{2\pi}{p}\right)] \quad (3)$$

The first discrete derivative in each direction is given by

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$$T \approx t(\frac{q_0 - q_c}{R}, \dots\dots\dots\dots, \frac{q_{p-1} - q_c}{R}) \qquad (4)$$

To achieve property which remains unchanged when a specified transformation is applied, step function is introduced

$$S(X) = \begin{cases} 1, & if \quad X \geq 1 \\ 0, & otherwise \end{cases} \qquad (5)$$

Hence substituting above values resulting function obtained

$$T \approx t(S(q_0 - q_c), \dots\dots\dots\dots, S(q_{p-1} - q_c))$$

Therefore, LBP code of a pixel (x_c, y_c) is generated for each neighbor by assigning binary weight

$$L_{P,R} = \sum_{p=0}^{p-1} s(q_p - q_c)\, 2^p$$

In $LBP_{P,R}$ the subscript represents using the operator in a (P,R) neighborhood.

4. GREY LEVEL CO-OCCURRENCE MATRIX (GLCM)

The GLCM is well familiar method for texture analysis and it is also known as Grey Level Spatial Dependency Matrix. It estimates image possessions collectively which are related to second order statistics. The functions of GLCM specifies the texture of an image by estimating probability of pixel's pairs with specific values and approaches towards special relationship happens in an image, obtains GLCM and then producing statistical measures from this matrix. These statistical measures in turn used to produce following statistics

Energy: $\sum_{x,y} p(x,y)^2$

Entropy: $-\sum_{x,y} p(x,y) \log p(x,y)$

Homogeneity: $\sum_{x,y} \frac{1}{1+(x-y)^2} P(x,y)$

Inertia: $\sum_{x,y} (x-y)^2 P(x,y)$

Correlation: $-\sum_{x,y} \frac{(x-\mu)(y-\mu)}{\sigma^2} P(x,y)$

Shade: $\sum_{x,y} (x+y-2\mu)^3 P(x,y)$

Prominence: $\sum_{x,y} (x+y-2\mu)^4 P(x,y)$

Variance: $\sum_{x,y} (x-\mu)^2 P(x,y)$

Where $\mu = \mu_i = \mu_j = \sum_x x \sum_y p(x,y) = \sum_y y \sum_x p(x,y)$

And $\sigma = \sum_x (x-\mu_i)^2 \sum_y P(x,y) = \sum_y (y-\mu_j)^2 \sum_x P(x,y)$

Here in GLCM properties; contrast measures the local variations in the grey level co-occurrence matrix, correlation determines the probability of pixel pairs that can occur, energy gives the uniformity by summing of squared elements in the GLCM. Homogeneity finds the closeness of elements in GLCM of the diagonal. Variance is a measure of the dispersion of the values around the mean. Entropy is similar to the variance.

5. DATASET CONSIDERED

In order to present the proposed model a dataset of facial images is considered from the standard facial repository 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.

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The paper also includes a review of basic articles from particular subject areas, where the aging database FG-NET was used and the presentation of standard results. The theme of this dataset is to present basis facts related to research activities in age estimation during the past, given an indication of the main methodologies acquired, present a comprehensive list of standard results and most importantly given roadmaps for time ahead, needs and research directions.
We enlighten the importance of experiments on FG-NET due to the following reasons:

1) FG-NET is very exacting for our task in two ways. First, it has much age gaps. The largest gap is 45 years in FG-NET, contrast with to 12 years in the passport databases. Second, the number of images of a subject is very limited, which makes learning very back-breaking.

2) Since FG-NET is an open source available dataset, experiments on FG-NET will serve as a standard/baseline for further studies on the topic.

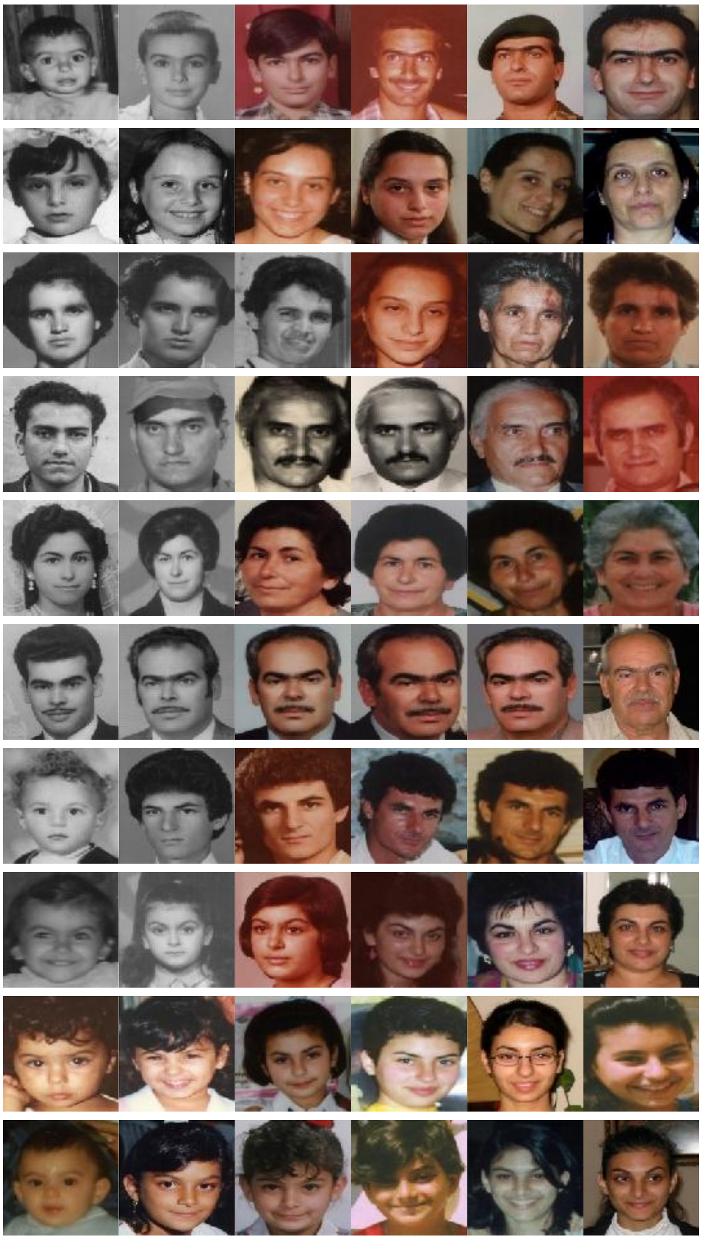

Fig.1. Sample images of 10 subjects at different ages from FG-NET dataset.

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6. METHODOLOGY:

Consider in order to implement the proposed method the experimentation is carried out in matlab environment. Each of the input images from the image dataset are considered, preprocessed such that they are free from noise. Each of the preprocessed image is considered and LBP features and GLCM features are extracted using the methodologies present in section 4 and 5 of the paper. These features are given as inputs for the model proposed in section 2 to obtain the PDF's (Probability Density Functions). During the texting phase, the above procedure is repeated and PDF's are identified. These PDF's are compared with that of the PDFs obtained during the training Section. The comparison is based on maximum likelihood estimate. The results are compared using the Classifier Accuracy by using the formula

CA = (Total number of pixels in the actual image/ Total number of pixels in the acquired image) *100

The accuracy is measured using Accuracy Exact Match (AEM) and is calculated using

$$Ai = \frac{T_I}{T_R} \times 100\%$$

Where T_I = number of exact match; T_{RI}= number of test images

The error is calculated using Actual Error (AEO), given by

$$A = \frac{T_C}{T_R} \times 100\%$$

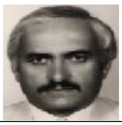
Here T_C= number of correct predictions; The accuracy is calculated by using

$$A = \frac{T_A}{T_R} \times 100\%$$

T_A = number of actual classification as true.

7. RESULTS

The results are computed for 15 images and they are depicted as follows

Image	**AEM in Percentage**	**AEO in percentage**	**ACC in percentage**
	34.3	68.1	66
	41.3	78.1	72.1
	47.3	81.2	70.2
	46.7	82.3	88.0
	43.4	83.6	74.4
	48.9	82.7	76.1

	44.1	88.4	77.2
	31.8	85.5	78.3
	33.7	86.5	76.5
	35.6	84.4	80.7
	38.9	85.5	81.6
	48.1	83.4	82.7
	43.4	82.3	84.3
	44.5	81.5	85.4
	43.6	82.4	86.2

8. CONCLUSION

In this article a methodology is highlighted for identification of the age by proposing a statistical mixture model namely BGMM. The methodology is tested using benchmark dataset and the results are analyzed using metrics such as AEM, AEO, ACC. From the above metrics it can be clearly seen that the developed method exhibits good acceptance state of around maximum 88%.

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