MANTECH Publications

Journal of Digital Image Processing and Computer Vision
Volume 2 Issue 3

Automatic Age Estimation Based on LBP and GLCM Features Using SVM

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Abstract

Face is generally considered as the reference frame of mind. Therefore, to estimate the feeling of the mind, many authors have considered the emotions from the facial expressions into consideration to identify the state of mind of an individual. Hence in this article we proposed a methodology for automatic age estimation based on Local Binary Pattern (LBP) and Grey Level Co-Occurrence Matrix (GLCM). The facial features are extracted using LBP and GLCM and these features are given as input's to the Support Vector Machine (SVM) for age estimation. The experimentation on proposed method is carried out using FG-NET database and Mean Absolute Error (MAE) is calculated to compare the proposed method with state-of-the-art algorithms. Finally, the proposed methodology demonstrates the classification accuracy above 88%.

Keywords: *Age estimation, Local Binary Pattern, Grey level Co-occurrence matrix, Support Vector Machine, Mean Absolute Error*

INTRODUCTION

The latest technological evolutions have forced the mankind to undergo different methodologies for communicating and storing of information. This information can be of public and private usage. Therefore, it is of vital importance to safeguard the private information and disclose the public

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information. With these considerations, many models are developed and utilized for effective communication with the very objective to transmit the information in a most secured manner. With the increase in the technological developments, latest evolutions have benefited the mankind on one end and laying roots for the intruders/hackers/unethical users to invade the information and conceal the private infor-mation/tamper the information. Therefore, misuse of the data has been increased considerably. With the wide growth in the information, the data available across the sources has increased and also the storage area necessary to hold this information has also increased exponentially. Therefore, it is a challenging task to derive methodologies that can behold the data so that the private information totally secured. With this back drop, many Mathematical Innovations based on Cryptographic Models have evolved [1],[2],[3]. However, these models can be effective in case of texture transactions where the text can be encrypted using different variable length keys and can be decrypted at the other end using the inverse process.

Therefore, the above said methodologies cannot identify the facial changes within the distributed environment. The present thesis aims at proposing and developing models that can help in effective retrieval of the faces irrespective of age and texture, skin tone etc. A Bivariate Gesture Mixture Model is considered for this purpose.

The related work done in this area is described according the methodologies. [4] thoroughly studied Label Distribution Learning (LDL) and Adaptive Label Distribution learning (ALDL) for the problem of insufficient training data with exact ages for facial age estimation and proposed an algorithm called Semi-Supervised Adaptive Label Distribution Learning(SALDL) to get the solution and also to improve the performance using unlabeled data for estimating age of a human by facial images. [5] presented a method for facial age estimation using binarized statistical image features (BSIF) and Local Binary Patterns (LBP).

The proposed method consists of three modules first is face preprocessing second, feature extraction and finally age estimation. Using BSIF and LBP methods the face ROI features are extracted and estimated the age by two classification algorithms one is LIBSVM for SVR and

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SimpleR for KRR. [6] presented a new method to classify age of facial image. The face features and shape are transferred into a set of land mark-terms which in turn used to produce weight matrix using TFIDF technology. In this technology the information retrieval and text mining fields is introduced. By processing LBP features density peaks were generated for each age group.

2. RELATED WORK

This study was proposed by Wendy S. Yambor, Bruce A. Draper, J. Ross Beveridge in the year 2000. It deals with the role of Eigen vectors election and Eigen space distance measures on PCA-based face recognition systems. The FERET face recognition evaluation studies created a large face database (1,196 subjects) and a baseline face recognition system for comparative evaluations, and these results were used in the study. A statistically significant improvement is observed for the Mahalanobis distance alone when compared to the other traditional distance measures as City-block, Euclidean, Angle. A set of experiments were conducted where the training (gallery) and testing (probe) images were selected randomly and Mahalanobis was again superior when 60% of the Eigen vectors were used. Although improvements maybe possible by combinations with L1, such improvements are likely to be small and these methods don't perform better than Mahalanobis alone. It examines questions of how many Eigenvectors to select and the according to what criteria, and also compares variations in performance due to different distance measures and number of Eigenvectors. Comparisons of the standard method for selecting a subset of Eigenvectors to one based on like-image similarity. While the like image method seemed like a good idea, it does not perform better in the study. This paper has been written by a couple of authors named Yun Fu and Nanning Zheng. It introduces the concept of appearance based photo realistic facial modeling. In other words, this technique is also called "Merging face" or in short it's called the M-face. There are two categories of object classes named Linear and Lambertian. While writing this paper it was assumed that the human face belongs to both the above cate-gories. Face space and attribute space are spanned respectively, making use of groups of prototypes and merging ratio image(MRI). The MRI is nothing but a mixture of individual expression ratio image, aging ratio image and illumination ratio image.

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An important aspect related to the development of face aging algorithms is the evaluation of the ability of such algorithms to produce accurate age-progressed faces. In most studies reported in the literature, the performance of face-aging systems is established based either on the judgment of human observers or by using machine-based evaluation methods. In this paper we perform an experimental evaluation that aims to assess the applicability of human-based against typical machine based performance evaluation methods. The results of our experiments indicate that machines can be more accurate in determining the performance of face-aging algorithms. Our work aims towards the development of a complete evaluation framework for age progression methodologies [7]. The topic of accurate performance evaluation for age progression methodologies is of utmost important for further development of this field. Due to the nature of the problem, standard performance evaluation metrics similar to the ones used in other face interpretation applications are not applicable to this problem. For that reason, most researchers working in the field rely on the judgment of human observers for evaluating their methods [8]. However, human-based evaluation is a time-consuming process that produces subjective results. In this paper we demonstrate that it is possible to replace human expertise with appropriate machine-based evaluation methodologies, in the task of performance evaluation of face-aging algorithms. By doing so it is possible to get improved and more accurate performance evaluation metrics using a fast, low cost process that can be used for large scale evaluation experi-ments. Our ultimate aim is to develop and use a complete framework for evaluating age progression methodologies. For this purpose, a standardized aging database containing samples from different ethnic origins and uniform age distribution across age groups will be required. The introduction of a standardized performance evaluation framework will enable the direct comparison of face-aging algorithms reported in the literature so that the most promising technologies will evolve.

3. METHODOLOGY

Consider in order to implement the proposed method the experimentation is carried out in matlab environ-ment. Each of the input images from the image dataset are considered, preprocessed such that they are

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free from noise. Each of the preprocessed image is consid-ered and LBP features and GLCM features are extracted using the methodologies present in section 2.1 and 2.2 of the paper. These features are given as inputs for the model proposed in section 2.3 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.

3.1 Feature Extraction

In the proposed methodology in order to estimate the age group, each facial image considered are proposed such that they are free from noise. Each facial image considered are first converted into gray scale. Each of the images are annotated into the frontal images using the model presented by Stansn et al for active shape. In this process the faces are normalized basing on the center point of eyes and each of the faces are rotated by different angles so that each image is normalized [9]. In order to normalize the faces, the angle of rotation may change and is calculated by using the formula.

$$\theta = \tan^{-1}\left(\frac{R_y - L_y}{R_x - L_x}\right)$$

where g_c denotes the gray level at the center pixel(X_c, Y_c), g_n represents the gray values of pixel. C defines the threshold value and is given by

$$C(X) = \begin{cases} 1, & if\ X \geq 0 \\ 0, & otherwise \end{cases}$$

3.2 Final Stage

Local Binary Pattern is used for classification in computer vision. In particular case of the texture spectrum model proposed in 1990 [10], [11]. 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

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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.

LBP code of a pixel (Xc, Yc) is generated for each neighbor by assigning binary weight

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

In LBP P, R the subscript represents using the operator in a (P, R) neighborhood.

3.3 Gray Level Co-occurrence Matrix

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 [12], 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
$\sigma = \sum_x (x-\mu_i)^2 \sum_y P(x,y) = \sum_y (y-\mu_j)^2 \sum_x P(x,y)$

3.4 Support Vector Machine

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples [13],[14].

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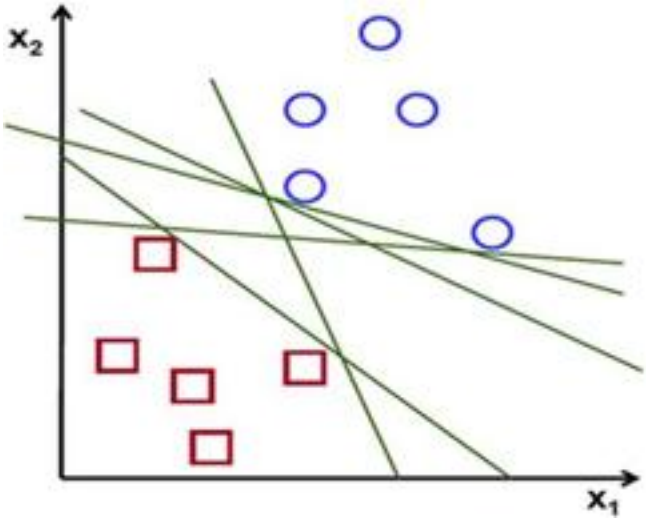


Figure: 1

4. RESULTS

Table 1 Values of the parameters that are generated from GLCM TE: Texture Energy FDS: Fractals

Sr. No	Entropy	Contrast	Correlation	Homogeneity	Energy	FDS	TE
1	6.68	232.24	0.91	0.28	0.000784	1.275	0.06
2	6.13	60.21	0.94	0.37	0.001407	1.134	0.12
3	6.45	94.61	0.93	0.34	0.001229	1.78594	0.14
4	7.28	83.93	0.94	0.31	0.001067	1.241204	0.16
5	7.23	76.47	0.95	0.34	0.001240	1.622346	0.13
6	7.88	32.55	0.94	0.38	0.001954	1.531308	0.13
7	7.64	46.35	0.96	0.27	0.000617	1.362582	0.13
8	6.47	100.25	0.92	0.27	0.000791	1.6948	0.10
9	7.73	55.70	0.95	0.29	0.000733	1.20771	0.11
10	7.34	95.96	0.94	0.31	0.001158	1.3652	0.12

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5. CONCLUSION

In this article a methodology is highlighted for identification of the age by proposing a statistical model. The methodology is tested using benchmark dataset and the results are analyzed using metrics such as TE and FDS. 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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