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Gender Classification from Facial Images Using LBP

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***Abstract*- Gender is an important demographic attribute of people. This project provides an approach to human gender recognition in computer vision using a facial recognition technique called Local Binary Patterns Histogram (LBPH). In this technique, the face area is divided into small regions from which local binary pattern (LBP) histograms are extracted and concatenated into a single vector efficiently representing a facial image. A working model has been created using a combination of Python and OpenCV, along with a multistage Haar Cascade Classifier in order to identify the major datapoints needed. The model, as well as a review of contemporary approaches exploiting information from facial images is presented. We highlight the advantages of using LBPH over Eigenfaces an Fisher Faces, besides the various challenges faced and survey the representative methods of these approaches. Based on the results, good performance has been achieved for datasets captured under controlled environments, but there is still much work that can be done to improve the robustness of gender recognition under real-life environments where various environmental conditions such as lighting, distance to subject, background etc. cannot be controlled.**

Index Terms- Accuracy, Gender Classification, LBP

I. INTRODUCTION

Gender recognition is an important task for human beings, as many social functions critically depend on the correct gender perception. Some major applications of automatic gender classification include intelligent user interface, surveillance, collecting demographic statistics for marketing, etc. The problem of gender classification from face images has received much interest in the last two decades.

Classification of gender is a two-class problem wherein the data is categorized as male or female. The task is relatively easy for humans as compared to machines. Humans can quickly determine gender from hairstyle, head or facial features such as iris [1], eyebrows [2], nose cheek bones and facial hair [3]. The variations in gender characteristics of face results in problems for machines. Similarly, during the image capturing process the factors of image quality like low resolution, dithering and noise also make image analysis a challenging task.

In the past two decades, several papers have been published on gender classification and these can be classified mainly into two groups based on the information they used:

1. Geometry based
2. Appearance-based methods.

Geometry based methods use distances between important points on the face such as eyes, nose, lips, chin and hair, also known as fiducial distances of a faces for gender classification [4,5].

Appearance-based methods use transformations or some other mathematical operations on the pixels of a face image such as Local Binary Patterns (LBP).

Generally speaking, the gender classification framework consists of five procedures:

Fig. 1 Gender Classification Framework

1. Input Image: The first step of gender classification is to obtain the raw data from various sources such as sensors, including camera (images, videos) [6] and voice recorder.
2. Pre-processing: Pre-processing is a procedure used to improve the quality of raw data, which includes the normalization of illumination, the extraction of the informative area. Pre-processing is also used for correcting imperfections such as filling holes, noise removal, face detection, etc. The undesired information is which results in an improvement in the identification accuracy rate.
3. Feature extraction: Feature extraction captures the main characters of the pre-processed signal

as the input parameter for the classification algorithm. [7]

4. Classification algorithm: This project addresses the problem of gender classification using LBP.
5. Evaluation: In this step the performance of the gender classification system is measured in terms of accuracy, which refers to the probability of correct recognition of a person as a male or a female.

II.APPLICATIONS

The development and progress in gender recognition technology has led to many potential uses in a large application scope, because the gender classification techniques can significantly improve the computer's perceptional and interactional capabilities. For example, gender classification improves the intelligence of a surveillance system, analyze the customers' demands for store management, and allow the robots to perceive gender, etc. To be more specific, applications of gender classification can be categorized in the following fields:

1. Human-Computer Interaction: Based on personalized information the system can provide customized services for users by adapting to them according to their gender [8].
2. Surveillance Systems: Gender classification in surveillance systems for public places (e.g., bank, school) can assist by tracking moving objects, detect abnormal behaviors, and facilitate investigation of criminals who try to hide their identity.
3. Demographic Research: Automatic identification of gender can enhance demographic statistics (e.g. gender, disability status, race definition) and population prediction. This acts as a supplementary method to demographic research conducted on the web or in public places.

III.LITERATURE SURVEY

Common classification algorithms used are k-nearest-neighbor, Fisherface, PCA, neural network, and SVMs. Moghaddam and Yang [9] used raw image pixels with nonlinear SVMs for gender classification on thumbnail faces (1221 pixels); their experiments on the FERET database (1,755 faces) demonstrated SVMs are superior to other classifiers, achieving the accuracy of 96.6%.

Ben Abdelkader and Griffin [10] exploited local region matching and holistic features with Linear Discriminant Analysis (LDA) and SVM for gender recognition. Local region-based SVM achieved the performance of 94.2% on the 12,964 frontal faces from multiple databases (FERET and PIE).

Beikos-Calfa et al. [11] proposed a holistic but resource intensive strategy that employed Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) for gender recognition, and reported 93.33% accuracy.

Golomb et al. [12] trained a gender classifier "SexNet" with a two-layer neural network on 90 facial images and achieved an accuracy of 91.9%.

Balci [13] used eigenfaces and trained a Muti-Layer Perceptron on FERET Dataset to analyze which eigenface contributed to gender classification.

Shakhnarovich et al. (2002) [14] made an early attempt by collecting over 3,500 face images from the web. On this difficult data set, using Harr-like features, they obtained the performance of 79.0% (Adaboost) and 75.5% (SVM).

M. Nazir et.al [15] implemented Discrete Cosine Transformation (DCT) technique for feature extraction and sorting the features with high variance. The KNN classifier using Euclidean distance to find closest neighbors. The different preprocessing techniques was used such as face detection. For face detection Viola and Jones method was used. Histogram equalization technique was used to stretch the contrast of the image and also used to overcome illumination variation in the image. These sorted coefficients are arranged in a vector and passed to the KNN classifier. The ratio of training and testing image is 50 to 50 for KNN classifier. Then the obtainable accuracy is 99.3%.

In the last decade a powerful way of texture description called local binary patterns (LBP) has been proposed for texture classification [16], face detection [17], and face recognition [18,19], which yielded a recognition rate of 97.9% on the FERET FA/FB image sets.

IV. RELATED WORK

Local Binary Pattern (LBP), introduced by Ojala [16], is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the 3 x 3 neighborhood of each pixel and considers the result as a binary number. It can be represented by LBP^{P}_{R} where P and R are corresponding to the total number of neighborhood pixels of a center pixel and radius. The histogram of these $256(2^8)$ different labels can then be used as a texture descriptor.

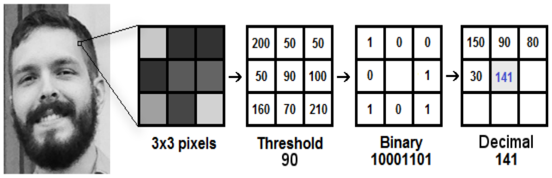

Fig. 2 LBP Computation

Formally, given a pixel (I_c) at (x_c,y_c), the resulting LBP can be expressed in the decimal form:

$$LBP\binom{P}{R}(I_c) = \sum_{n=0}^{P-1} s(I_n - I_c)2^n$$

Where, I_c and I_n are the grey-level values of the central pixel and the surrounding pixel, and s(x) is 1 if x>=0 and 0 otherwise. After obtaining the LBP labeled image $f_l(x,y)$, the LBP histogram can be defined as

$$H_i = \sum_{x,y} I\,\{f_l(x,y) = i\}, i = 0,1,\ldots,n-1$$

where n is the number of different labels produced by the LBP operator, and I{A} is 1 if A is true and 0 if A is false.

V.PROPOSED SYSTEM

In this work, we combined frontal face datasets of faces94 together for gender classification which contains 600 male faces and 600 female faces. The number of training images and labels was 340. The total number of test images was 86, which contained 34 subjects. The number of male and female faces were 43 each. We normalized these faces into 180× 225 resolution. We applied LBP operator on each non overlapping blocks of a face and obtained histograms of it. The histograms of all block LBPs of a face are concatenated to form a single feature descriptor for gender classification. This feature descriptor describes the texture of the given face.

We trained the classifier on labeled faces of dataset and tested by performing 10-fold cross validation. In k-Fold Cross-Validation a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The process is repeated k times, with each of the k subsamples used exactly once as the validation data. A single estimation is then produced by averaging the k number of results from the folds.

VI.CONCLUSION

In this paper, we investigated gender classification on faces acquired in constrained conditions. The simplicity and efficiency of LBP allow for very fast feature extraction. The regional and global descriptions of LBP allow for capturing multi-view information of faces. The experimental results show that classification accuracies are highly improved and a highest correct rate is 100% on the face database faces94.

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REFERENCES

[1] Vince Thomas, Nitesh V Chawla, Kevin W Bowyer, and Patrick J Flynn. Learning to predict gender from iris images. In Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007. First IEEE International Conference on, pages 1–5. IEEE, 2007

[2] Yujie Dong and Damon L Woodard. Eyebrow shape-based features for biometric recognition and gender classification: A feasibility study. In

Biometrics (IJCB), 2011 International Joint Conference on, pages 1-8. IEEE, 2011.

[3] Vicki Bruce, A Mike Burton, Elias Hanna, Pat Healey, Oli Mason, Anne Coombes, Rick Fright, and Alf Linney. Sex discrimination: how do we tell the difference between male and female faces? Perception, 1993.

[4] J. M. Fellous, Gender discrimination and prediction on the basis of facial metric information, Vision Research, vol. 37, no. 14, pp. 19611973, 1997

[5] S. Mozaffari, H. Behravan, and R. Akbari, Gender Classification Using Single Frontal Image Per Person: Combination of Appearance and Geometric Based Features, in 2010 20th International Conference on Pattern Recognition, 2010, pp. 1192-1195

[6] Sajid Ali Khan, Maqsood Ahmad, Muhammad Nazir, and Naveed Riaz. A comparative analysis of gender classification techniques. Middle-East Journal of Scientific Research, 20 (1):01–13,2014

[7] https://www.researchgate.net/publication/280105452_Human_Gender_Classification_A_Review

[8] Jürgen HP Hoffmeyer-Zlotnik and Christof Wolf. Advances in cross-national comparison: A European working book for demographic and socio-economic variables. Springer Science &Business Media, 2003.

[9] Moghaddam, B., Yang, M., 2002. Learning gender with support faces. IEEE Trans.Pattern Anal. Machine Intell. 24 (5), 707–711.

[10] Ben Abdelkader, C., Griffin, P., 2005. A local region-based approach to gender classification from face images. In: IEEE Conf. on Computer Vision and Pattern Recognition Workshop, pp. 52–52.

[11] J. Bekios-Calfa, J. M. Buenaposada, and L. Baumela, "Revisiting linear discriminant techniques in gender recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, pp. 858–864, Apr 2011.

[12] B.A. Golomb, D.T. Lawrence, and T. J. Sejnowski: "SEXNET: A Neural Network Identifies Sex from Human Faces". NIPS 1990.

[13] K. Balci, V. Atalay: PCA for Gender Estimation: Which Eigenvectors Contribute? ICPR 2002

[14] Shakhnarovich, G., Viola, P.A., Moghaddam, B., 2002. A unified learning framework for real time face detection and classification. In: IEEE International Conf. on Automatic Face & Gesture Recognition (FG), pp. 14–21

[15] M. Nazir, Muhammad Ishtiaq, Anab Batool, M. Arfan Jaffar, and Anwar M. Mirza., "Feature Selection for Efficient Gender Classification," In proc. WSEA international conference on Fuzzy systems, pp. 70-75, 2010.

[16] Ojala, T., Pietik¨ainen, M., M¨aenp¨a¨a, T.: Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (2002) 971-987

[17] Jin, H.L, Liu, Q. S., Tong, X. F.: Face Detection Using Improved LBP Under Bayesian Framework. In: Proceedings of the Third International Conference on Image and Graphics (ICIG 04), Hong Kong, China, 18-20 Dec (2004) 306-309

[18] Ahonen, T., Hadid, A., Pietik¨ainen, M.: Face Recognition with Local Binary Patterns. In: Proceedings of the European Conference on Computer Vision (2004)469-481

[19] Zhang, G.C.: Boosting Local Binary Pattern (LBP)-Based Face Recognition. In: Proceedings of the Sinobiometrics 2004, LNCS 3338 (2004) 179-186