Gender Recognition Based on Edge Histogram

A. R. Ardakany, *Member, IACSIT* and A. M. Joula

***Abstract*—In this paper, we present a novel method to gender classification using a new simple feature extraction which extracts geometric and appearance features at the same time. This feature extraction is performed by computing the derivative in all pixels of face images and then constructing a histogram based on edges magnitudes and directions. The experiments clearly show that the presented method is quite competitive with 95.67% accuracy on FERET database. In addition, the efficiency of the proposed method makes it a good choice for real-time systems which combine face detection and gender classification.**

***Index Terms*—Gender recognition; feature extraction; edges; histogram; FERET database.**

I. Introduction

Face is a very important biometric feature of human. Automatic recognizing and analyzing of face is one of challenging tasks in object recognition. Successful performing this task allows many applications in human computer interaction, psychology, security purposes and etc [1]. Useful information can be obtained from face images such as ethnicity, identity, age, gender, expression and so on [2], [3].

Gender plays a significant role in our interactions in society and with computers [4]. Actually Gender classification is a binary classification problem in which one has to predict an image belongs to a man or woman. It is an easy job for a person but a challenging one for computers [5]. Gender classification from face images has received much attention recently because of its applications including improving search engine retrieval accuracy, demographic data collection, human–computer interfaces (adjusting the software behavior with respect to the user gender) and etc [6]. Moreover it can be used as a preprocessing step for face recognition since it may halve the number of face candidates (in case of equal amount of both genders) before the recognition and thus causes the face recognition process almost twice faster [1].

Similar to other pattern classification problems, two key steps for gender classification are feature extraction and pattern classification. From the view of feature extraction, there are four kinds of methods. First kind of methods and simplest of them is using gray-scale or color pixel vectors as features [7]. Subspace transformation theory present some approaches such as PCA, ICA and LDA that we consider them as second kind of methods. These methods recognize objects after casting them into a low-dimensional space [8]. Disadvantage of this batch is that their efficiency is sensitive to face orientation and they don't work well if variation be large enough [9]. Third kind of methods is to use texture information like winkle and complexion [10]. Last kind of methods is extracting the local facial features for classification such as the analysis of facial winkles and shapes [9]. This is done with combining the facial feature detection with wavelet transform [11], [12].

From the view of classifier learning many different methods have been tried. We introduce some of them briefly here. [13], [14] used a two-layer network that the first layer was for feature extraction and the second for classification. Neural network which [14] used from called SexNet. [15] experimented with radial basis function (RBF) networks and inductive decision tress. In [16] maximum-likelihood system is used for face detection and the superiority of nonlinear SVMs over traditional linear pattern classifiers together with RBFs and large ensemble-RBF networks is showed. Accuracy that was achieved on the FERET face database in [16] was high (96.62%). In [17] classification is done by Gaussian process classifiers, which belong to Beyesian kernel classifiers classes. This method solves the problem of determining parameters for the kernels in SVMs. [18] tried to improve generalization for gender classification using fuzzy SVM. Another method which is used for gender classification is Adaboost. [19] applied a threshold Adaboost trained classifier for gender and ethnicity classification. Look up table (LUT) based weak classifier Adaboost is used in [20]. [21] used pixel comparison operators with Adaboost on low resolution grayscale face images and achieved over 93% gender classification accuracy. [22], [1] combined face detection and gender classification and carried out a comparison study for the state-of-the-art gender classification methods. Small differences in the classification rates between the methods were seen in results. In addition it was showed that combining the outputs of different gender classifiers can improve the classification rate [1].

In this paper, we present a fast and reliable method that is capable of classifying genders based on a simple feature extraction. The efficiency of the proposed method makes it a good choice for real-time systems which combine face detection and gender classification.

The rest of this paper is organized as follows: the next section contains a description of the proposed method including a description of the feature extraction used; In section 3, the proposed method is tested on the FERET database and compared against competing state-of-the-art algorithm described in [9]; In Section 4, the results are analyzed and lastly, conclusions are drawn in Section 5.

Manuscript received February 15, 2012; revised March 25, 2012.

Abbas Roayaei Ardakany is with University of Nevada, Reno (e-mail: roayaei@yahoo.com).

Amin Moaven Joula is with the Department of Computer Engineering, Sharif University of Technology, Tehran.

II. Edge Histogram

There are a lot of geometric differences between men and women faces. Thus, using face geometric features besides the appearance or texture features seems to increase gender classification accuracy. Accordingly, we have separate geometric and appearance feature extraction phases in the methods that make use of both feature types.

One of the approaches to use face geometric information is extracting face perimeter and components. Then we can use the distances between components or the gradient in specific locations to produce geometric features. The disadvantages of this approach are its complexity and time consuming training. Also having separate phases for extracting geometric and appearance features can impose extra time for the whole system especially in the training phase.

In this paper, we propose a gender classification method which defines its features based on edges magnitude and direction. In our method geometric and appearance features are extracted simultaneously. These features include necessary information for gender recognition. We show that, since our purpose is only to discriminate between male and female, we can achieve acceptable classification accuracy by only using frequency of edges distribution.

First, we obtain derivative map for the input image. This map can represent texture and edges and therefore geometric features at the same time.

Vertical and horizontal edge maps are computed in all pixels by convolving the masks $[-1,0,1]$ and $[-1,0,1]^{\mathrm{T}}$ with the original image. Consider d_x and d_y are the vertical and horizontal edge values in pixel (x, y), respectively. Then, the edge map direction and magnitude are obtained by (1) and (2) respectively.

$$\theta = tan^{-1}\left(\frac{d_y}{d_x}\right) \tag{1}$$

$$m = \sqrt{(d_x)^2 + \left(d_y\right)^2} \tag{2}$$

As a result, we have two matrices, magnitude and direction with the same dimension as the input image. The first one represents pixels derivative's magnitude and the second one represents the corresponding direction. Then, continuous values of magnitude and direction matrices are transformed into discrete values. The directions obtained from (1) are discretized to N primary directions (0, N-1). Likewise, the magnitudes are encoded to (0, M). In fact, the continuous space is transformed to fuzzy space. By increasing M or N smaller patterns can be represented.

Now, we define a histogram on the input image with number of bins equals to the number of possible (m, θ) pairs. So, each pixel in the edge image with magnitude m and direction θ is assigned to the bin number (m-1) × N+θ+1. All (0, θ) pairs are assigned to the bin number zero. Then, the histogram is normalized in order to become scale invariant. Accordingly, the proposed feature extraction algorithm is invariant to face image size and there is no need for resizing face images as a pre-processing procedure.

III. Experiments

A. The Dataset

FERET [23] is a large-scale face database which currently contains 11,383 pose images of 994 individuals.

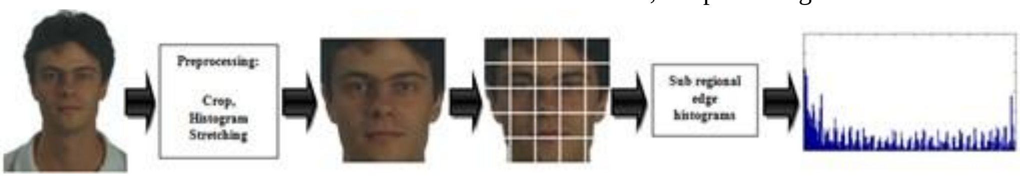


Fig. 1. Feature extraction steps

In this database, there are thousands of samples with 12 different poses. In this work, we use frontal face images (fa) which includes 1364 images from 994 individuals. Table 1 shows the database in detail.

TABLE I: Details of Feret Database

Database	Original size	Total number	Number of individuals	Female	Male
FERET	512×768	1364	994	504	860

B. Pre-processing

Preprocessing for gender recognition may include image resizing, normalization based on intensity, or geometric normalization. Geometric normalization consists of eyes localization and then applying geometric transformation so that each face image has eyes in the same location and all the faces are in the upright position. As noted in [1] normalization process may be useless if it is not carried out in a reliable way. Since the normalization implies further processing and usually does not have a good precision, and also in conflict with our desired algorithm that must be fast enough to support real-time systems, our approach in this paper does not use normalization

C. Feature Extraction

For extracting features, the edge histogram must be computed for each face image. We choose M=10 and N=8 as fixed parameters and Therefore, the histogram has (10-1) × 8+8+1=81 bins. This histogram contains information about the distribution of the local patterns over the whole image, such as edges, spots and flat areas.

For efficient face representation, one should retain also spatial information. For this purpose the image is divided into K×K separate regions R11, R12, R13,…, Rkk.

Then, the input image is divided into K×K equal size blocks where K is ranged from 1 to 9 and the histogram is computed in each block separately. Finally, these sub-regional histograms are concatenated into a single feature histogram. The process of feature extraction is illustrated in Figure 1.

For extracting face coordination from database images, Viola Jones [24] face detection algorithm is used. After feature extraction, the number of dimensions is decreased by applying PCA method.

D. Classifiers

In this paper, for evaluating the performance of the proposed method, three classifiers LDA, Adaboost, and SVM are used. We use MATLAB implementation of LDA with default parameters, Weka [25] implementation of Real-Adaboost with default parameters and LIBSVM [26] implementation of SVM with linear kernel and fixed parameter C=100.

IV. Results and Discussion

SVM with linear kernel, LDA and Adaboost classifiers are chosen to evaluate the performance of our proposed method. We use 10-fold cross validation method [27] for training the classifiers. The results are shown in figure 2.

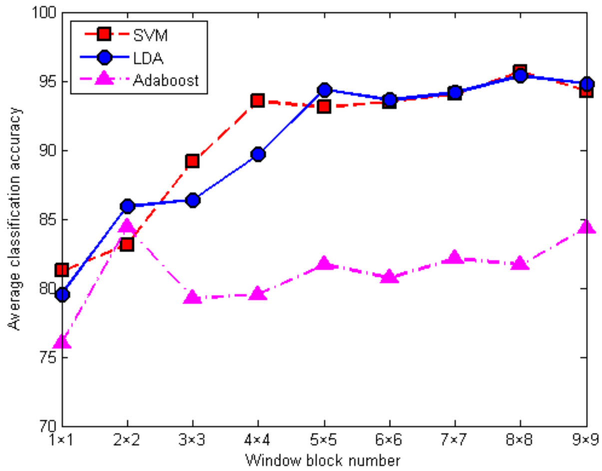


Fig. 2. Results for SVM, LDA, and Adaboost methods

According to the results, SVM with linear kernel and K=8 has the best outcome and we choose it as the optimum method. The detailed result for this optimum method is shown in table 2.

TABLE II: Results of the Optimum Method

	Total number	Correctly classified	Incorrectly classified	Accuracy
Male	860	840	20	97.61%
Female	504	465	39	91.61%

We also compare the proposed method with existing approach [9]. In the existing approach [9] Local Binary Pattern [28] is used for extracting texture features. LBP is a powerful way of texture description. The operator labels the pixels of an image by thresholding the 3×3-neighbourhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor. The most important difference between the proposed method and the existing approach [9] is that in our work the histogram is defined based on magnitude and direction of edges while the existing approach defines its histogram based on intensity of pixels. The classification results for both methods are shown in figure 3.

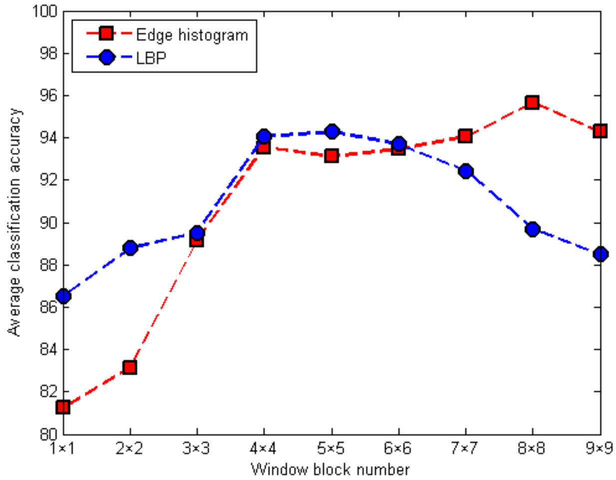


Fig. 3. Results of the proposed method and existing method in [9]

The results show that the proposed method has slightly better classification accuracy than the LBP method. As it can be seen, while we increase the number of divisions, the classification accuracy increases accordingly.

The reason is that when K is small, the histogram only contains local appearance and geometric features but while K increases, the spatial information are retained and consequently the accuracy is increased.

For proving the capability of the algorithm in fast feature extraction, we implement it as a real-time gender recognition system (figure 4) using OpenCV 2.1 [29] for face detection.

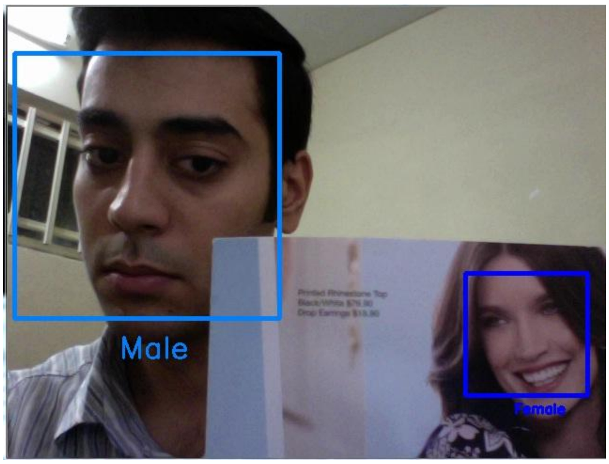


Fig. 4. Implementation of Edge-Histogram algorithm using OpenCV 2.1.

V. Conclusion

In this paper, a new gender classification method with high accuracy is proposed. In our work, feature extraction consists of producing a histogram based on magnitude and direction of edges in the face image. We concluded that in the performed experiments, as our purpose is only to discriminate between male and female, we can achieve excellent classification accuracy just by using simple feature extraction.

The efficiency and simplicity of our proposed method (Edge Histogram) result in a very fast feature extraction. Besides, regional and global descriptions allow for capturing geometric and appearance information of faces simultaneously.

REFERENCES

[1] E. Mäkinen and R. Raisamo, "An experimental comparison of gender classification methods," *Pattern Recognition Letters*, vol. 29, pp. 1544-1556, 2008.

[2] B. Wu, H. Ai, and Ch. Huang, "Real-time gender classification," 2003, pp. 498-503

[3] N. Sun, W. Zheng, Ch. Sun, C. Zou, and L. Zhao, "Gender Classification Based on Boosting Local Binary Pattern," in *Advances in Neural Networks* - ISNN 2006. vol. 3972, J. Wang, et al., Eds., ed.: Springer Berlin / Heidelberg, 2006, pp. 194-201.

[4] J. Wu, W.A.P. Smith, and E.R. Hancock, "Semi-supervised Feature Selection for Gender Classification," in *Computer Vision – ACCV* 2009. vol. 5995, H. Zha, et al., Eds., ed.: Springer Berlin / Heidelberg, 2010, pp. 23-33.

[5] Z. Xu, L. Lu, and P. Shi, "A hybrid approach to gender classification from face images," in *Pattern Recognition*, 2008. ICPR 2008. 19th *International Conference* on, 2008, pp. 1-4.

[6] L. A. Alexandre, "Gender recognition: A multiscale decision fusion approach," *Pattern Recognition Letters*, vol. 31, pp. 1422-1427, 2010.

[7] B. Moghaddam and M.-H. Yang, "Gender Classification with Support Vector Machines," *presented at the Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition 2000*, 2000.

[8] K. Balci and V. Atalay, "PCA for Gender Estimation: Which Eigenvectors Contribute?" presented at the Proceedings of the 16 th *International Conference on Pattern Recognition* (ICPR'02) 2002.

[9] H.-C. Lian and B.-L. Lu, "Multi-view Gender Classification Using Local Binary Patterns and Support Vector Machines," in Advances in Neural Networks - ISNN 2006. vol. 3972, J. Wang, et al., Eds., ed.: Springer Berlin / Heidelberg, 2006, pp. 202-209.

[10] R. Iga, K. Izumi, H. Hayashi, G. Fukano, and T. Ohtani, "A gender and age estimation system from face images," in *SICE 2003 Annual Conference*, 2003, pp. 756-761.

[11] S. Hosoi, E. Takikawa, and M. Kawade, "Ethnicity estimation with facial images," in *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*, 2004, pp. 195-200.

[12] H.-C. Lian, B. Lu, E. Takikawa, and S. Hosoi, "Gender Recognition Using a Min-Max Modular Support Vector Machine," in *Advances in Natural Computation*. vol. 3611, L. Wang, et al., Eds., ed.: Springer Berlin / Heidelberg, 2005, pp. 438-441.

[13] M. K. Fleming and G. W. Cottrell. "Categorization of faces using unsupervised feature extraction". 1990 IJCNN, vol.2, pages: 65-70.

[14] B. Golomb, D. Lawrence, and T. Sejnowski, "SexNet: A neural network identifies sex from human faces," *presented at the Proceedings of the 1990 conference on Advances in neural information processing systems 3, Denver, Colorado, United States*, 1990.

[15] S. Gutta, J. R. J. Huang, P. Jonathon, and H. Wechsler, "Mixture of experts for classification of gender, ethnic origin, and pose of human faces," *Neural Networks, IEEE Transactions* on, vol. 11, pp. 948-960, 2000.

[16] B. Moghaddam and Y. Ming-Hsuan, "Learning gender with support faces," *Pattern Analysis and Machine Intelligence, IEEE Transactions* on, vol. 24, pp. 707-711, 2002.

[17] A. M. Burton, V. Bruce, and N. Dench, "What's the difference between men and women? Evidence from facial measurement," Perception, vol. 22, pp. 153-176, 1993.

[18] L. XueMing and W. YiDing, "Improving generalization for gender classification," in *Image Processing*, 2008. ICIP 2008. 15th *IEEE International Conference* on, 2008, pp. 1656-1659.

[19] G. Shakhnarovich, P. Viola, and B. Moghaddam, "A unified learning framework for real time face detection and classification," in *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference* on, 2002, pp. 14-21.

[20] B. Wu, H. Ai, and C. Huang, "LUT-Based Adaboost for Gender Classification," in *Audio- and Video-Based Biometric Person Authentication*. vol. 2688, J. Kittler and M. Nixon, Eds., ed.: Springer Berlin / Heidelberg, 2003, pp. 1062-1062.

[21] S. Baluja and H. Rowley, "Boosting Sex Identification Performance," *International Journal of Computer Vision*, vol. 71, pp. 111-119, 2007.

[22] M. k. Erno, "Evaluation of Gender Classification Methods with Automatically Detected and Aligned Faces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, pp. 541-547, 2008.

[23] P. Phillips, H. Moon, S. Rizvi, and P. Rauss, "The FERET evaluation methodology for face-recognition algorithms," *Pattern Analysis and Machine Intelligence, IEEE Transactions* on, vol. 22, pp. 1090-1104, 2000.

[24] P. Viola and M. Jones, "Robust Real-time Object Detection," *International Journal of Computer Vision - to appear*, 2002.

[25] M. Hall, F. Frank, E. Holmes, B. Pfahringer, P. Reutemann, and H. Ian, "The WEKA data mining software: an update," *SIGKDD Explor. Newsl*, vol. 11, pp. 10-18, 2009.

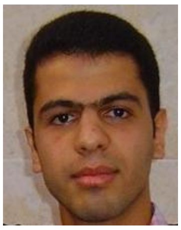
[26] C.-C. Chang and C.-J. Lin. "LIBSVM: A Library for Support Vector Machines". 2001.

[27] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," *presented at the Proceedings of the 14th international joint conference on Artificial intelligence* - Volume 2, Montreal, Quebec, Canada, 1995.

[28] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," *Pattern Recognition*, vol. 29, pp. 51-59, 1996.

[29] G. Bradski and A. Kaehler, Learning OpenCV: *Computer Vision with the OpenCV Library*: O'Reilly Media, 2008.

Abbas Roayaei Ardakany received his B.S. in Computer engineering from Sharif University of Technology, Tehran, in 2008, the M.S. in computer engineering from Shahid Chamran University, Ahwaz, in 2011. He is currently pursuing Doctoral programme at University of Nevada, Reno. He is the author/co-author of five publications in technical journals and conferences. His area of interest includes image processing, computer vision, genetic algorithm, and machine learning.



Amin Moaven Joula received a BS with honors from the Shahid Chamran University, Ahwaz, in 2010. He is currently a M.S. student in the Department of Computer Engineering at Sharif University of Technology, Tehran. His research interests are in computer vision, machine learning, pattern recognition, image processing, computational intelligence. His work has spanned a range of topics in vision including gender recognition, scene an image classification, image representation, image segmentation and face detection.