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GENDER CLASSIFICATION BASED ON FACIAL FEATURES

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Abstract-- The main objective of our project is Gender Classification with various facial images using image processing technique. Now-a-days gender classification plays an important role in biometrics, human computer interactions and demographic collections etc. The proposed gender classification system consists of face detection, feature extraction and Gender classification. In this project face is detected by using Viola-Jones Algorithm. Then Zernike Moments are used to extract the shape and edge features from face images. Zernike moments have rotational invariant property. It makes them suitable for many application. Zernike moments are accurate descriptors even with small size feature vector. This feature vector of training and testing images are given to Support Vector Machine. It classifies the given images as male or female.

Keywords—Face detection, Feature extraction, Zernike moments, SVM classifier , Gender Recognition

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I. INTRODUCTION

Gender classification is a fundamental task for human beings, as many social functions critically depend on the correct gender perception. Human faces provide important visual information for gender perception. The facial information is one by which human can make difference between men and women. However, in real-world applications, gender classification needs to be performed on real-life face images captured in unconstrained scenarios. Gender recognition in real-life faces is much more challenging compared to the case for faces captured in constrained environments. First faces are detected from facial images using Viola Jones algorithm[1]. Then features are extracted from detected faces using Zernike Moments[2], used for shape and edge analysis. The proposed method was evaluated using FEI and faces94 data- bases. The simulation results indicate the effectiveness of the method in achieving the greater accuracy even under the variations in pose, scale, rotation and occlusion. Gender recognition is a complex task as the face image of a man and woman differ in shape and also in texture. Also an facial image is subjected to variations in appearance, pose, illumination, position and expression. The gender classification can be categorized into geometric and appearance based methods. In geometric method, the features are based on the structural information of the face like distance between various points on face that include eyes, nose, mouth, chin and outline of the head. Appearance based methods are holistic that considers all the pixel values from the face image i.e., the information is extracted from the entire face. Though it is advantageous for considering the complete face, it is sensitive to variations in the facial image. Thus a suitable method has to be devised that is invariant to these constraints. Different objects have different shapes and edge .It is therefore desirable to represent objects using both shape and edge information. From the features extracted classification is done by using some classifiers like SVM, KNN, decision tree, multiclass SVM etc. The classifiers are typically trained using large sets of labeled training examples. So that it can easily classify the data points when testing examples are provided. Experiments were conducted on different set of face databases such as FEI, ORL, faces94 datasets. The overall performance critically depends on three elements feature set, classifier, training set.

II. METHODOLOGY

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A .*Proposed Method*

The methodology of the proposed system to classify the genders is as shown in Fig. 1. A new method is proposed for gender recognition by extracting feature vectors. For training face images feature vectors are obtained by calculating moments[1]. Then SVM classifiers are trained by using this feature vectors of training image. Similarly, feature vector are calculated for testing images. Then a set of testing face images are given to the classifier in order to classify the given test face images as male or female. In this paper binary images are used for extracting the feature vectors instead of gray scale image. Because binary images gives the shape and edge features of an image.Therefore RGB image is converted into gray scale image and this is converted into binary image by using thresholding.

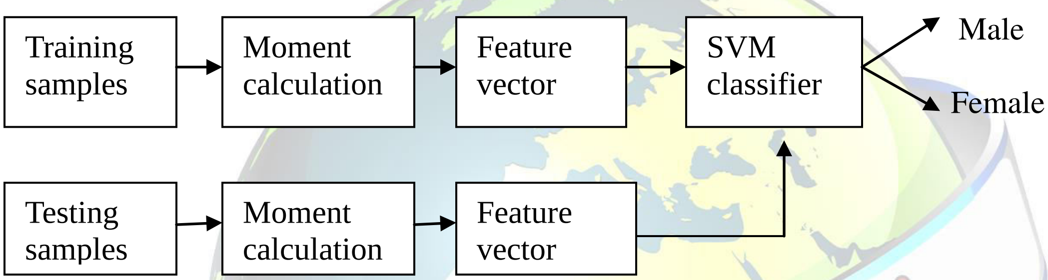

Fig. 1. Proposed gender classification system

B. Feature Extraction using Global Zernike Feature

Zernike moment has better capability to describe the facial features. The Zernike polynomials[4] are orthogonal, they can describe image features without redundancy or overlap in the information transferred between different moments. Calculation of Zernike moments from the input image includes three steps. They are calculating the radial polynomials, calculating the Zernike basic functions and calculating the Zernike moments[5] through projecting the input image onto the Zernike basic functions. The first step is calculating the one dimensional Zernike radial polynomials which are defined as

$$R_{n,m}(\rho)=\sum_{s=0}^{(n-|m|)/2}(-1)^{s}\frac{(n-s)!}{s!\left(\left(\frac{n+|m|}{2}\right)-s\right)!\left(\left(\frac{n-|m|}{2}\right)-s\right)!}\rho^{n-2s}$$

Where ρ is the distance between the center of image and corresponding point , n is a non-negative integer which demonstrates the order of the radial polynomial and m is the azimuthal angle repetition which must satisfy n-|m|=even and |m|≤n.[6]

The Zernike basic function is given as

$$Z_{n,m}(x,y)=R_{n,m}(\rho_{xy})e^{-jm\theta_{xy}}$$

Where the equations used for obtaining the distance ρ_{xy} and the phase θ_{xy} for pixel (x,y) are [7]

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$$\rho_{xy} = \frac{\sqrt{(2x-N+1)^2+(N-1-2y)^2}}{N}$$

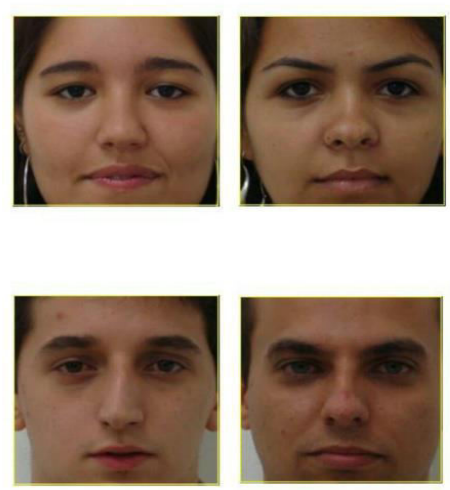
$$\theta_{xy} = \tan^{-1}\left(\frac{N-1-2y}{2x-N+1}\right)$$

C. Classification

The Support Vector Machine (SVM) as a classifier has been used more often in the gender classification problem and has been proved that it is superior in pattern classification[8]. An SVM classifier is a linear classifier where the separating hyper plane is chosen to minimize the expected classification error of the unseen test patterns[9]. It takes feature vectors extracted from images as input and it gives the class this image belongs to (Males, Females) as its output. It maximizes the prediction accuracy and it is a kernel based approach and the accuracy of the SVM is affected by the kind of the kernel function has been chosen and using a suitable kernel may lead to good accuracy .In this approach , the kernel of the SVM classifier is fixed at 5 x 5.

SVM is a strong classifier which can identify two classes. SVM classifies the test image to the class which has the maximum distance to the closest point in the training. SVM training algorithm built a model that predict whether the test image fall into this class or another. SVM classifier is a binary classifier which looks for an optimal hyperplane as a decision function.Once trained on images containing some particular object, the SVM classifier can make decision regarding the presence of an object, such as a human, in additional test images The operation of the SVM algorithm is based on finding the hyperplane that gives the largest minimum distance to the training examples.Twice, this distance receives the important name of margin within SVM's theory. Therefore the optimal separating hyperplane maximizes the margin of the training data.

1. Sample dataset for training



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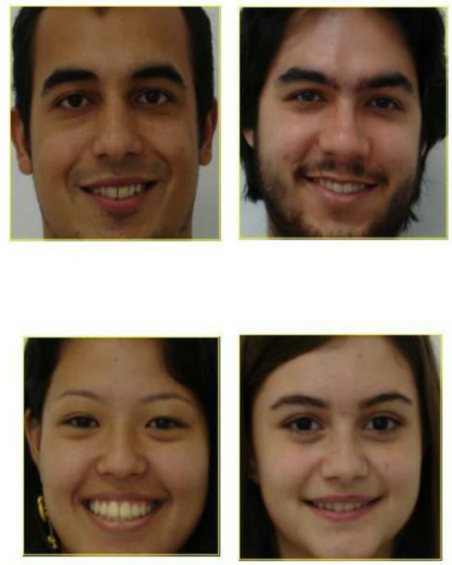

2.Sample dataset for testing

D.*Result Analysis*

DATASET	TRANING SAMPLES		TESTING SAMPLES		CORRECTLY CLASSIIED	ACCURACY
FEI	Male	Female	Male	Female		
	20	20	20	20	36	90
ORL	Male	Female	Male	Female		
	20	20	20	20	34	85
ORL	Male	Female	Male	Female		
	40	40	20	20	38	95

Conclusion

This paper put forward a new frame in gender recognition from face image features. This work applies global feature descriptor model for gender recognition. Global Zernike Feature descriptors are concatenated to form a 5 dimensional feature vectors. These 5 feature vectors are applied to the SVM classifier for gender recognition. This method robustly gives excellent performance in recognizing the gender

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under various conditions like facial expressions, illumination, pose variation and occlusions. The accuracy rate for this gender recognition method has been increased in comparing with the existing new methods and it takes less amount of time to detect the gender because of using a few number of higher order moments for gender classification.

REERENCES

[1].]. Arnold W, Madasu V K, Boles W W and Yarlagadda P K 2007 A feature based face Yarlagadda P K 2007 A feature based face recognition techniqueusing Zernike moments,Proc. RNSA Security Technology Conference, 341–345.

[2].Singh, C., Walia, E., Upneja, R.: Accurate calculation of Zernike moments. Inf. Sci. 233,255–275 (2013)

[3].Chen, W.-S., Lee, P.-Y., Hsieh, L.: Gender classification of face with moment descriptors. In:The Eighth International Multi-Conference on Computing in the Global InformationTechnology, ICCGI2013 (2013).

[4].Çoban, B.S., Gökmen, M.: Gender classification with local Zernike moments and local binary patterns. In: 2014 22nd Signal Processing and Communications Applications Conference (SIU), pp. 1475–1478. IEEE, April 2014.

[5]. Mahesh, V.G., Raj, A.N.: Invariant face recognition using Zernike moments combined with feed forward neural network. Int. J. Biom. 7(3), 286–307 (2015)

[6]. N. Farajzadeh, K. Faez and G. Pan, "Study on the performance of moments as invariant descriptors for practical face recognition systems",IET, vol.4, pp.272-285, 2010.

[7]. Abdolhossein Fathi , Pendar Alirezazadeh, Fardin Abdali-Mohammadi , "A new Global-Gabor-Zernike feature descriptor and its application to face recognition" Elsevier-2016.

[8] B. Moghaddam and M.-H. Yang, "Gender Classification with Support Vector Machines," *Proc. Int'l Conf. Automatic Face and Gesture Recognition,* pp. 306-311,Mar. 2000.

[9] Support Vector Machines for Classifying Face Data David Shaw Due:12/14/2009.

