Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Emerging Trends and Innovations in Electronics and Communication Engineering - ETIECE-2017

Volume 5, Special Issue 01, Jan.-2018 (UGC Approved)

Face Based Gender Classification Using COSFIRE Filter

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Abstract- *One of the most important factors influencing the social activities of a human is his/her gender. Due the importance of a person's gender, we present a study and analysis of a gender classification based on human face. Gender classification from facial images has numerous applications and can be used in marketing, retail advertising and security systems. We propose a novel system for classifying the gender of a person from face. For face we propose a descriptor based on COSFIRE filter.Artificial Neural Networks are information processing systems with certain characteristics similar to the working of a human neuron and unlike conventional machines it learns by example and not by an algorithmic approach and Artificial Neural Network has been used as the classification model. We demonstrate the effectiveness of the proposed approach on a dataset of GENDER-FERETdataset and achieve an accuracy of about 89%.*

Keywords-COSFIRE Filter, Gabor Filters, Gait, Gender Classification. Trainable Filters.

I.INTRODUCTION

Even in today's modern world Gender of a person continues to be the most influential factors affecting the social interactions of a person. Automatic classification of gender continues be open source of research as it has gained vast interest in the previous years.
Gender classification from facial images is an open field of learning in both applied research as well as fundamental applications. Gender classification is a two-class pattern recognition problem [1]. From the fundamental point of view, it is very puzzling as to how humans recognize the gender of a person so effortlessly and rapidly, but the same task for a computer vision algorithm is very challenging. Many applications such as biometric systems are making successful use of facial image analysis. Gender classification systems do not offer same level of accuracy and performance as compared to the face detection systems [1]. The difficulties for a pattern recognition algorithm in gender classification arise from variations in the images captured by the camera [2], the intrinsic difference between the faces of the people and due to the occlusions from sunglasses, hats, scarves.
In this paper we propose a novel gender classification system based on facial images, the system makes use of a trainable COSFIRE filter and an Artificial Neural Network. Such a system has vast applications in today's modern-day world where the interaction between the two genders is limitless but how so ever for safeguarding the integrity of a gender there are certain places which have to be restricted to a specific gender only. One of the most important application of a gender classification system is securing of a particular area, service to the specified gender only. Such a system can be used effectively and efficiently in public areas or transportation systems where entry of a certain gender is allowed and thus may also be used for helping the cause of female molestation. Such a system can also be used in smart marketing, online web privacy etc.

II. LITERATURE REVIEW

Fig. 1 illustrates the average face of a male as well as a female which have been generated from the FERET dataset [2]. From these average faces many differences between the male and female faces were observed. Differences in the intensity distribution values specially near the eye and hair regions have compelled many researchers to use the intensity pixel value to form a binary classifier [3,4].Due to the softer facial features of women as compared to that of the men there are certain textural differences as well. Women have prominent eyebrows where as men have rough skin, such differences in the textures can be best described by Histograms of Local Binary Patterns [5,6].Shape of a women's face is round while that of a male is much more elliptical such features were exploited by the researchers to propose a Gender Classification system using Histogram of Gradients [7].Fiducial distances are the distances between certain landmarks of the face. While considering these distances the average face of a man has closer eyes, thinner nose. These fiducial points may be tracked using deep learning or shape models [8,9].

Figure 1: Average Face of (a) Man (b) Women

Detecting faces from video streams or images having multiple no of persons in them is one of the most challenging tasks in object detection. The problem has been greatly solved by Viola-Jones object detection framework which is the first competitive object detection frame work for real time working [10,11]. Viola-Jones Algorithm makes use of 'Haar Feature Selection'for creating an 'internalimage' A combination of weak classifiers is used to construct a strong classifier to form a learning algorithm and at the end a cascaded architecture is used where in each stage consists of a strong classifier. Much work on face detection has been proposed in [12]. An AdaBoost classifier is used with Haar and Local Binary Patterns where as a SVM classifier has been used with HOG features [12].Much research has been done on classifying the gender of a person using different methods and most of the approaches show a promising solution to this pattern recognition problem. An approach using ICA and SVM was proposed in 2005 by Jain et.al [13]. Different classifier namely COSINE classifier, Linear Discriminant classifier and SVM were used for separating the features of males and females [13]. The experiment was done on FERET gender dataset with an accuracy of 96%.

Erno Makinen and Roope Raisamo experimented on IIMand FERET database for automatic gender classification [14]. The experiment consisted of four automatic alignment methods and four different gender classification models.

PCA, LDA and Subclass Discriminant Analysis on a dataset of 8112 images was done by Tejas et.al [15]. This work was very important as the result showed linear discriminant functions provide good generalization capability with limited no of training samples as the images being used were in the form of heterogeneous data.

Global and Feature based Gender Classification from faces was implemented by Samarasena Buchala et.al. PCA, CCA and SOM were used for the implementation of the experiment [16]. Different parts of face like eyes, nose or sometimes the whole image was used. The results showed that PCA gives recognition rate of 87.5% as compared to other methods.

Discrete Cosine Transform was implemented on Stanford University Medical Student (SUMS) frontal facial images database by M. Nazir et.al. A KNN classifier using the Euclidean distance to find the closest neighbors [17]. This system is one of the most accurate systems with an accuracy rate of 99.3% when the ratio of training to testing samples is 50 to 50.

A hybrid system using global and local features was created by ZiyiXu et.al. [18]. Global features were extracted using AdaBoost algorithm were as for local feature extraction AAM was used.

III. IMPLEMENTATION

Through this paper we propose a novel system based on COSFIRE (Combination of Shifted Filter Responses) for automatic classification of human gender from face images. Contour Detection [19], retinal vessel segmentation [20], object localization and recognition [21], and handwritten digit classification [22] tasks are being done very effectively using a COSFIRE filter.

COSFIRE filters are trainable shape detectors its selectivity is determined in an automatic configuration process, analyzing the shape properties of a given prototype pattern of interest [23].

FERET-GAIT dataset is a standard database for facial recognition system evolution. A database of facial imagery was collected between December 1993 and August 1996. In 2003 DARPA released a high-resolution, 24-bit color version of these images. The dataset tested includes 2,413 still facial images, representing 856 individuals.

The proposed technique has been divided into the following steps;

1) Pre-Processing

As already discussed in the above mentioned sections face detection is one the main issues in gender classification using face. Face detection in any gender classification framework using face images is important since image of the whole body is captured by the system and to locate multiple faces that may be present in a video stream. Viola-Jones object detection frame work has been used for face detection. Two Haar features have been used for detecting the face. However, if the faces are readily available from an image the image is rescaled to 128 by 128 pixels. Figure 2 shows the detected faces of a male and female from the FERET dataset.

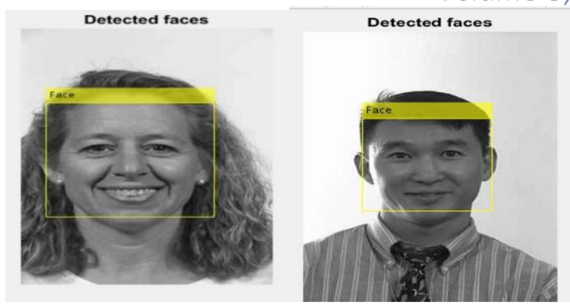

Figure 2: Detected Face (a) A Female (b) A Male

2) COSFIRE Filter Configuration

As already stated the selectivity of a COSFIRE filter is determined in an automatic configuration process. For the configuration of a COSFIRE Filter; first a bank of Gabor filters is applied. These are applied for various orientations and scales to the given prototype image. In the next step a set of concentric circles is considered and chooses maximum Gabor response along these circles around the prototype image. Four parameter values are determined for each local maximum point i, namely: λ_i(scale), ϑ_I (orientation) of the Gabor filter that achieves maximum response at that position along the polar coordinates. The parameter values of all points are grouped in a set of 4 tuples [23]:

$$S_f = \{(\lambda_i, \vartheta_I, \rho_i, \varphi_i)\ i=1\ldots\ldots\ldots n\} \text{--------------------}(1)$$

In equation 1 f denotes the given prototype pattern whereas n denotes the number of local maximum points.

An image of a face from FERET dataset is shown in Fig. 3a. The COSFIRE filter is configured using the encircled region as a prototype. The superimposed response maps of a bank of Gabor filters used in the configuration stage is shown in Fig. 3b. In Fig. 3c we represent the resulting COSFIRE filter structure.

3) COSFIRE Filter Response

By combining the response of the involved Gabor filters in the set S_f we compute the response of the COSFIRE filter. A Gabor filter with scale λ_i and an orientation θ_i is applied for each tuple i is set S_f. In the next step we consider the Gabor responses at the locations indicated by ρ_i, φ_i and here we apply a multi-variate function to these responses for obtaining the COSFIRE filter response in every location of input image. The Gabor response maps are also blurred by taking the maximum of their neighboring responsesweightedbyGaussianfunction maps and for allowing some tolerance. The white blobs in Fig. 3c indicate the Gaussian function maps. Theblurredandshifted Gaborfilterresponses are combined for computing the COSFIRE filter response rS_f at a location (x, y)is given by geometric mean [23];

$$rS_f = \left(\prod_{i=1}^{n} s\,\lambda_i, \theta_{i,}, \rho_i, \varphi_i(x, y)\right)^{1/n} \text{----------------------}(2)$$

An inverted response to Fig. 2a is shown in Fig. 2d, this image is an inverted response map of the configured COSFIRE filter.

4) Face Descriptor

The maximum response of a collection of COSFIRE filters that are selective for different parts of a face form a descriptor for the face images. In Fig. 3a COSFIRE filter configured and selective for central region of lips is shown. Similarly, other parts of the face may be used to configure more COSFIRE filters. For a given test image all the COSFIRE filters are applied and a spatial pyramid of three levels is applied.

In level zero only tile is considered which of the size of the image, in level one pyramid the face is divided into four sections or we may say four tiles having 2*2 spatial arrangement are considered, similarly in level two a spatial arrangement of 4*4 is considered with 16 tiles as shown in Fig. 4.

For each tile the maximum response of the COSFIRE filter is considered, hence for k no of COSFIRE filters we obtain a k element vector. In our case we have a 21k element vector.

5) Classification Model

The face descriptors obtained from the COSFIRE filter are employed for training an Artificial Neural Network.

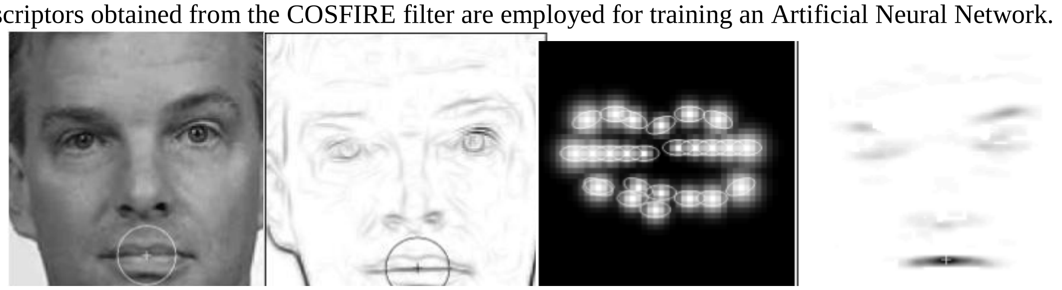

Figure 3a: A training face, with encircled pattern of interest. Figure 3b: Superimposed Response Maps.Figure 3c: Structure of COSFIRE Filter. Figure 3d: Inverted Response Map of the Concerned COSFIRE Filter.

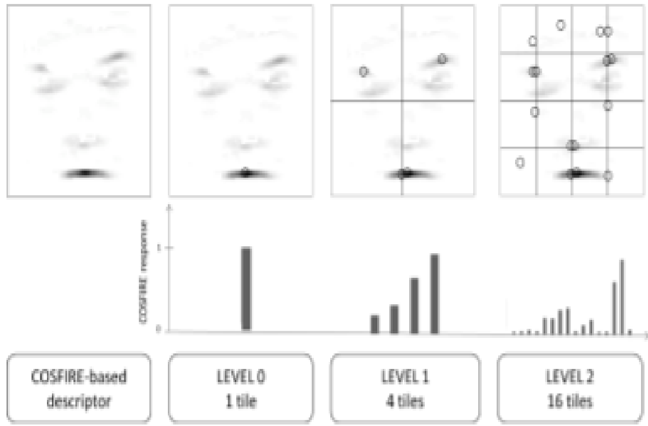

Figure 4: Three Level Spatial Pyramid System

For trainingthe neural network first the no of COSFIRE operators is chosen after this the facial image is subjected to face detection however if the face is readily available from an image it is resized to 128 by 128 pixels. COSFIRE operators for the training database images is calculated as described in the previous sections and the network is trained using these descriptors.

IV. RESULTS

Supervised Training Model was used for training the Neural Network, in this scheme an output is presented for each input and the network learns by example.

An epoch is a measure that tells how many times all the training vectors are used to update the weights of the network. During the training of the Neural Network it was seen that an optimum no of Epochs had to be chosen for training as using lesser number would result in under-fitting whereas using lesser no of epochs would result in over-fitting.

Also, it was observed that the ratio of training and testing samples should be optimum as using too many testing samples would result in the network memorizing the outputs and would behave in a unspecified mannerhow so ever if less no of training samples are provided then the network is not able to learn properly and hence results in undesired operation.

While testing the Neural Net it was seen that most of the images from FERET-GENDER dataset were correctly classified. As discussed in the sections above different features of interest were extracted and used for automatic gender classification.

Also a few images of the FERET dataset have been wrongly classified this is due to the different postures, expressions and color of the skin.

While plotting the ROC of the proposed system it is seen that the accuracy of the system goes in increasing with the increasing no of COSFIRE filters but after a certain point it remains constant and does not show any increase.

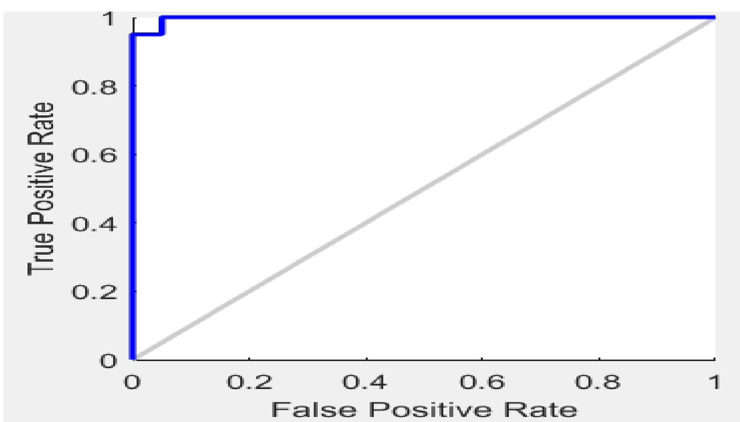

Figure 5: ROC

Figure 5 shows the experimental results in the form of accuracy. Here the training set and the testing set accuracy have been combined and merged together.

V. CONCLUSION & FUTURE WORK

The proposed model for gender classification is based on Trainable COSFIRE filters and combined with an Artificial Neural Network based on Back-propagation model and the proposed system is highly accurate in classifying the gender of a person from face images in frontal view.
In future gender of a person can be classified using a different classification model such as SVM or Fuzzy measures. Also for increasing the accuracy of the proposed model for gender classification a multimodal system approach can be used where in more than one quantifiable feature of a person may be extracted and used for gender classification.

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