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An Assimilated Face Recognition System With effective Gender Recognition Rate

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***Abstract*— Gender Recognition in Face Recognition System has prevalent applications in the fields of demographic data collection, video surveillance, security, retail advertising and marketing and it also plays a vital role on object recognition in robot research area, which has shown an intensive attention in the past few years.However, face recognition is still a challenging task since face images are easily confused by changes of the facial factors, such as illumination, pose, the different expressions, or glasses. The goal of this paper is to improve the effectiveness of gender recognition when there are affected(blurred) images in the dataset. We applied novel descriptor based COSFIRE filters to achieve the Gender Recognition[1] in the Face Recognition System. A COSFIRE filter is trainable, in that its selectivity is determined in an automatic configuration process that analyses a given prototype pattern of interest on FERET training set. Extensive experiments were conducted on the GENDER-FERET dataset which contains 474 training and 472 test samples and demonstrated robustness and effectiveness of the proposed model. It also outperforms an approach that relies on handcrafted features and an ensemble of classifiers.**

***Index Terms*— Gender Recognition, Face Recognition System,COSFIRE filters, Local Binary Patterns, LFW, SVM Classifier, Histogram of Gradients, GENDER-FERET dataset, Euclidean Distance,Sparse Regularization Discriminant Analysis.**

I. INTRODUCTION

Face Recognitionis a popularchallenging task in robot vision and Pattern Recognitionand has many practical applications including security surveillance and face positioning.Gender recognition[4] belongs to the category of Pattern Recognition.It is very intriguing to understand how gender recognition is an effortless operationfor human beings which is done very rapidly, but for a computer vision algorithm the task could be very challenging. The difficulties emerge from the possible variations of a face captured by a camera[5], which depend on the image acquisition process (pose of the face, image illumination and contrast, background), the intrinsic differences between people's faces (expression, age, race), as well as the occlusions (sunglasses, scarves, hats). From the applied research point of view, there is a commercial interest to have systems that can automatically recognize the gender from face images.

Examples include surveillance systems that can assist to restrict areas to one gender only, faster processing in biometrics systems that rely on face recognition, custom user interfaces depending on the gender of the person interacting with them, smart billboards designed to attract the attention of male or female audience, and systems for the collection of data in support of market analysis.

Based on these observations, many researchers use the pixel intensity values of the faces to train a binary classifier for gender recognition.

Further differences can be observed in terms of texture. This could be due to the softer facial features of women and more pronounced eyebrows, while men have a rougher skin especially in the presence of beard. The most popular texture descriptors for face images are the histograms of local binary patterns (LBP).

One may also observe a variation in the shape of the face. The face of a woman is generally more rounded, while the face of a man is more elliptical. In few research papers, the authors exploited this aspect and proposed the use of Histogram Of Gradients (HOG)[28] descriptor for the recognition of gender. In other works, shape-based features have been combined with other types of features in order to have a more robust classifier [23] [14] [3] [8].

Finally, there are also many subtle differences in the geometry of the faces. The average face of a man has closer eyes, a thinner nose and a narrower mouth. These observations triggered the investigation of what are known as facial fiducial distances, which are essentially the distances between certain facial landmarks (e.g. nose, eyes contour, eyebrows)[36] . The fiducial points[24]may be detected using active shape model or deep learning techniques[15][16].

We propose to use trainable Combination Of Shifted FIlter REsponses (COSFIRE) filters[17] [4] for gender recognition[1] from face images. COSFIRE filters have already been found to be highly effective in different computer vision tasks, including contour detection[21] [9]retinal vessel segmentation [10]object localization and

recognition[18] [11],and handwritten digit classification[19]. COSFIRE filters are trainable shape detectors. The term trainable refers to the ability of determining their selectivity in an automatic configuration process that analyses a given prototype pattern of interest in terms of its dominant orientations and their mutual spatial arrangement. Our hypothesis is that by configuring multiple COSFIRE filters that are selective for different parts of the faces we can capture the subtle differences that distinguish the faces of men and women.
Therestisorganizedasfollows.Somerelatedworksabout dimensional reduction for face recognition are reviewed in section 2. The proposed Assimilated Face Recognition algorithm is introduced in Section 3. In section 4 the experimental results performed on the training images.Finally,inSection5,we gave conclusionsabout our experimental results.

II.RELATED WORKS

In the early work, traditional algorithms including Eigenface and Fisherface were main approaches for face recognition and had achieved significant performance. Eigenfacewasoptimalforfacereconstructionandusedin robot vision fluently, however, it cannot extract abundant discrimination information. Belhumeur et al., proposed Fisherface which considers discrimination information maximization. However, when face samples near the individual boundaries, it is not the ideal algorithm to discriminating differentface.
Currently, subspace based algorithms[2], which can also be classified into two categories: sparse representation based algorithms and manifold learning based algorithms. Sparserepresentation is the widely used dimensional reduction tool for face recognition. Classical sparse representation based algorithms including Sparse Regularization Discriminant Analysis (SRDA) preserved the sparse structure of the original space. Specifically, SRDA considered discriminating efficiency and sparse representation structure simultaneously. However, sparse representation based algorithms struggle to achieve optimal performance when there contain confused samples in the dataset.

III.PROPOSED METHOD

In the following we give an overview of the trainableCOSFIRE filter approach and show how we use it to form facedescriptors. For further technical details on COSFIRE filterswe refer the reader to.

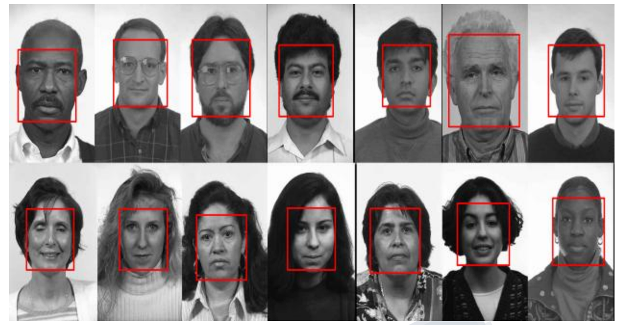

Fig 1:Examples of face images in the GENDER-FERET dataset[35]. The square boxes indicate the faces detections by Viola-Jones Algorithm

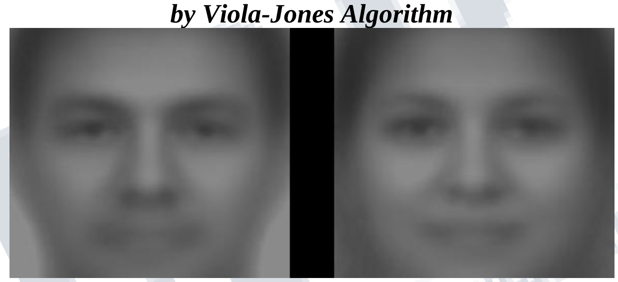

Fig 2: The average face of (a) Men and (b) Women computed from a subset of the FERET Database as shown in Fig 1.

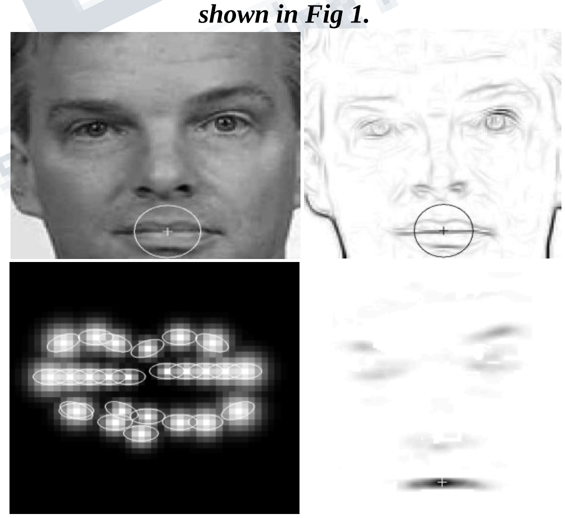

Fig 3: (a) A training face image of size 128 x 128 pixels. (b) The superimposed (inverted) response maps of a bank of Gabor filters with 16 orientations ($\theta = \{0, \pi/8, \pi/4, \ldots 15\pi/8\}$ and a single scale $\lambda=4$. (c) The structure of a COSFIRE filter for pattern shown in (a). (d) The (inverted) response map of the concerned COSFIRE filter to the input image in (a).

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In Fig. 1, we load a subset of FERET database which contains 7 Male and 7 Female images with reference with Viola-Jones algorithm (red color border of face detection).
In Fig 2, we calculated average of training images and Female images shown in Fig. 1 and segregated as per the gender.Based on these observations[25], many researchers use the pixelintensity values[29] of the faces to train a binary classifier for gender recognition [31].
In Fig. 3a, we show an image of a face. We use the encircled region as a prototype to configure a COSFIRE filter to be selective for the same and similar patterns[20].The most popular texturedescriptors[26] for face images are the histograms of LocalBinary Patterns (LBP)[32].
In Fig. 3b we show the superimposed response maps of a bank of Gabor filters which is used in the configuration stage and in Fig. 3c we illustrate the structure of the resulting COSFIRE filter. The ellipses[13] represent the properties of the determined contour parts. Their sizes and orientationsindicate the parameters λ_iand θ_iof the concerned Gabor filters.
In Fig. 3c the white blobs indicate the Gaussian function maps that are used to blur the response maps of the corresponding Gabor filters.
In Fig. 3d we illustrate the (inverted) response map of the configured COSFIRE filter to the image in Fig. 3a. For clarity purposes the zero values are rendered as white pixels and the non-zero values are rendered as shades of gray.
Here, the encircled region indicates a prototype pattern of interest. The plus marker indicates the center of the prototype.

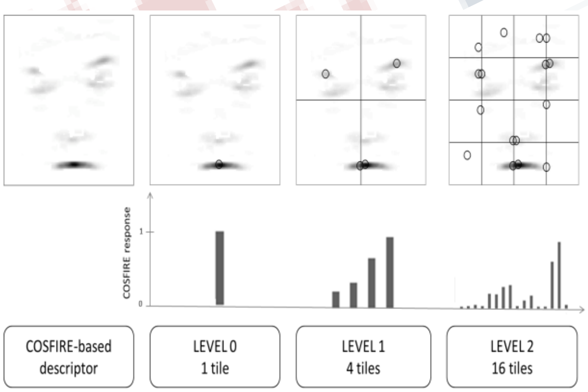

Fig 4: Example of the COSFIRE face descriptor using a singlefilter.

The circles indicate the locations of the maximum filterresponses in a three-level spatial pyramid, while the bar plots representthe values of the maximum responses.
Fig. 4 shows the computation of the 21-element vector after the application of a single filter.

A. COSFIRE Filter Configuration

The selectivity of a COSFIRE filter is determined in an automatic configuration process that analyses the shape properties of a given prototype pattern of interest. This procedure consists of the following steps.

First, it applies a bank of Gabor filters of different orientations and scales to the given prototype image. Second, it considers a set of concentric circles around the prototype center and chooses the local maximum Gabor responses along these circles. The number of circles and their radii values are given by the user. For each local maximum point $i$the configuration procedure determines four parameter values; the scale $\boldsymbol{\lambda_i}$, and the orientation $\boldsymbol{\theta_i}$of the Gabor filter that achieves the maximum response at that position, along with the polar coordinates ($\boldsymbol{\rho}_i$; $\boldsymbol{\phi}_i$) with respect to the prototype center. Finally, it groups the parameter values of all points in a set of 4-tuples:

$$S_f = \{(\boldsymbol{\lambda_i}, \boldsymbol{\theta_i}, \boldsymbol{\rho}_i, \boldsymbol{\phi}_i) \mid i = 1, 2, \ldots \mathrm{n}\} \tag{1}$$

Where $f$denotes the given prototype pattern and n represents the number of local maximum points. We explain the function of the white blobs in the next section.

B. COSFIRE filter response

The response of a COSFIRE filter is computed by combiningthe responses of the involved Gabor filters indicatedin the set S_f . For each tuple i in S_f a Gabor filter with a scale $\boldsymbol{\lambda_i}$and an orientation $\boldsymbol{\theta_i}$ is applied. Then, the nextstep considers the respective Gabor responses at the locationsindicated by the polar coordinates ($\boldsymbol{\rho}_i$; $\boldsymbol{\phi}_i$) and appliesa multivariatefunction to them to obtain a COSFIRE responsein every location $(\boldsymbol{x}, \boldsymbol{y})$ of an input image. For efficiencypurposes, in practice the Gabor response maps areshifted by the corresponding distance parameter value $\boldsymbol{\rho}_i$inthe direction opposite to $\boldsymbol{\phi}_i$. In this way, all the concernedGabor responses meet at the support center of the filter.

In order to allow for some tolerance with respect tothe preferred positions, the Gabor response maps are alsoblurred by taking the maximum of their neighboringresponsesweighted by Gaussian function maps. The standarddeviation σ_i of such a Gaussian function depends linearlyon the distance $\rho_i$from the support center:

$$\sigma_i = \sigma_0 + \alpha\rho_i$$

Where σ_0 and α are constants determined empirically on thetraining set.

The standard deviations of theGaussian functions increase with increasing distance fromthe support center of the COSFIRE filter.

Finally, the response of a COSFIRE filter r_{S_f} in a location(x; y) is achieved by combining the blurred and shiftedGabor filter responses $\mathbf{S}_{\lambda_i,\theta_i,\rho_i,\phi_i}(\mathbf{x},\mathbf{y})$ by geometric mean:

$$r_{S_f} = \left(\prod_{i=1}^{n} \mathbf{S}_{\lambda_i,\theta_i,\rho_i,\phi_i}(\mathbf{x},\mathbf{y})\right)^{\frac{1}{n}} \quad (2)$$

If thepixel is darker, then the COSFIRE response is very high. Themaximum response is correctly obtained in the center of theprototype that was used to configure the concerned COSFIREfilter. The filter, however, achieves other responses(lower than the maximum) to patterns that are similar to theprototype. In general, the filter responds to features thatconsist of a horizontal edge surrounded by two curvaturespointing outwards.

C. Face descriptor

We form a descriptor for face images by using the maximumresponses of a collection of COSFIRE filters that areselective for different parts of a face. In the example illustratedin Fig. 3 we demonstrate the configuration and applicationof one COSFIRE filter that is selective for the centralregion of the lips. Similarly, we may use other parts of the face to configure more COSFIRE filters. For a given testimage we then apply all COSFIRE filters and consider aspatial pyramid of three levels. In level zero we consideronly one tile, which is the same size of the given image, inlevel one we consider four tiles in a $2 \, x \, 2$ spatial arrangementand in level two we consider 16 tiles in a $4 \, x \, 4$ grid.

For each of the 21 tiles we take the maximum value ofevery COSFIRE filter. This means that for k COSFIRE filtersthe descriptor results in a $21k$-element vector. We normalizeto unit length the set of k COSFIRE filter responsesin each tile.

The proposed approach that use the responses of multipleCOSFIRE filters for the description of a face is inspiredby the hypothesis of population coding in neuroscience.Neurophysiologists believe that a shape is described by thecollective response of a set of shape-selective neurons in visualcortex[33].Further inspiration was obtained from thespatial pyramid matching approach with bags of features [27].

D. Classification model

We use the resulting descriptors from the images in agiven training set to learn an SVM classification model withthe following chi-squared kernel $K(x_i, y_j)$:

$$K(x_i, y_j) = \frac{(x_i - y_j)^2}{\frac{1}{2}(x_i + y_j) + \in} \quad (3)$$

Where x_i and y_j are the descriptors of training images i and j, and the parameter $\in$ represents a very small value (eps in MATLAB) in orderto avoid division by zero errors. In practice, we use the $libsvm$ library [22] with the above mentioned custom kerneland for the remaining parameters we use the default values.

E.Gender Detection

For the descriptor that is based on raw pixels we learned anSVM with a linear kernel. For the HOG- and LBP-based descriptorsthat generated histograms of features, we learnedan SVM with a histogram intersection kernel for each ofthem. We evaluated all possible combinations of these threetypes of features by fusing the results of the correspondingSVM classifiers. Fusion was achieved by summing up thecorresponding output probabilities of the classifiers.

If thetotal male probability was larger than the total female probabilitythen the image was classified as a man(Male), otherwise itwas classified as a woman(Female).

IV. EXPERIMENTAL RESULTS

We applied COSFIRE filters for Gender Recognition purpose using GENDER-FERET dataset which contains 474 training and 472 test samples and this data set with reference to the Viola-Jones algorithm [27] [30] to every image in the dataset and resized the detected faces to a fixed size of 128 x128 pixels.

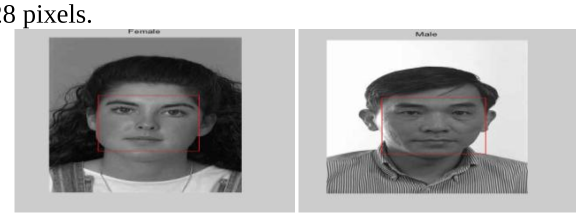

Fig 5: (a) Female recognized image (b) Male Recognized image obtained after classifier applied with the FERET dataset.

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Fig 6(a): Training data of 10 different poses of single male.

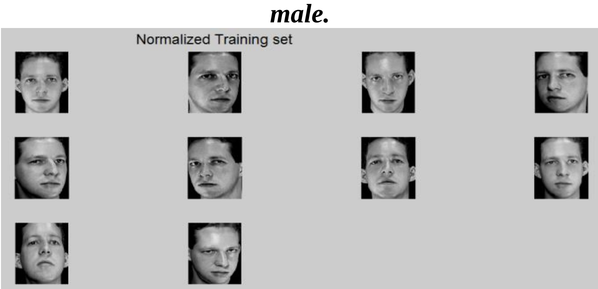

Fig 6 (b): Normalization of the trained images(with improved illumination

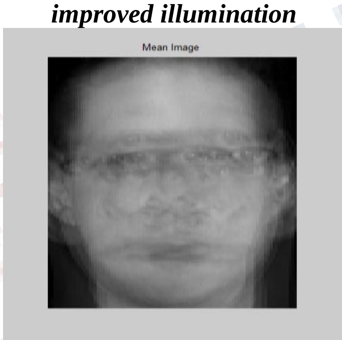

Fig 6(c): Mean(Average) Image of all 10 normalized images.

Fig 6 (d):Eigen faces of mean image.

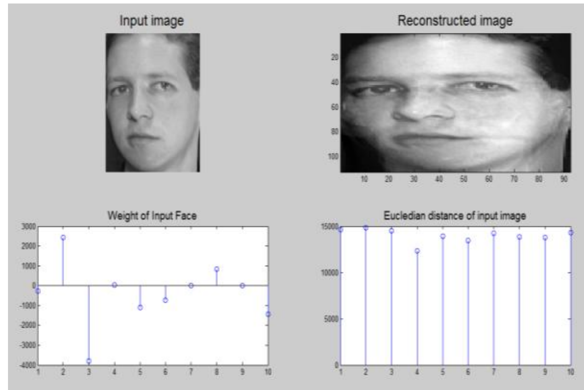

Fig 6 (e):Recognized Image for available Query(input) image in the training dataset

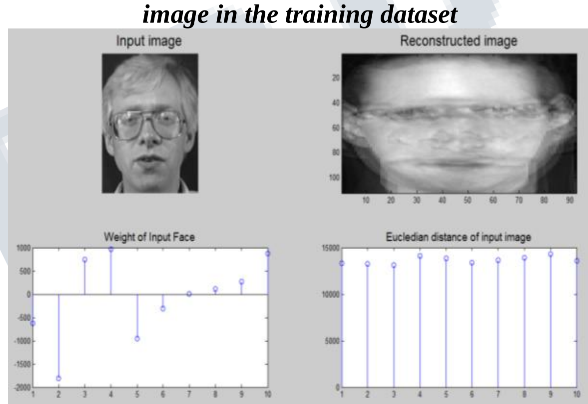

Fig 6 (f):Recognized image for unavailable Query(input) image in the training dataset

We performed analysis of Face Recognition using Euclidean Distance Classifier. For this, we took 10 training set images as in fig 6(a) and normalized them to improve the illumination with the results plotted in 6(b). Then we calculated the Mean of the normalized images and Eigenfaces of corresponding mean images in 6(c) and 6(d) respectively. Finally, we obtained Reconstructed images and calculated Euclidean distance for available and unavailable images in 6(e) and 6(f) respectively.

V.CONCLUSION

In this paper, we recognized Gender using the GENDER-FERET dataset. The proposed method that is based on the trainable COSFIREfilters and combined with an SVM classifier of a chi-squaredkernel is highly effective for gender recognition from faceimages. It outperforms an ensemble of three classifiers thatrely on the HOG and LBP handcrafted features along withthe raw pixel values.The approach is suitable for various image classificationtasks.

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