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Facial Gender Analysis using Gabor-DWT Feature Extraction Method

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Abstract: ***Facial Gender Analysis has application of specific gender entry detection, human machine interface for digital marketing, real time targeted advertisement and gender demographic analysis. The facial gender can be predicted by classification of the texture and unique edges pattern. Gabor filter can extract the edge- texture patterns on the face but has problem of high dimensionality with redundancy. For accuracy enhancement, the dimension and redundancy is needed to reduce by proposed technique as maxDWT feature optimization method. The proposed model is evaluated on real life challenging dataset of face as illumination variation, POSE, face profile, age variation and obstruction on face as hat, birthmark, moles, speckles, beard, etc. Results shows that proposed technique far better than existing state of art methods of gender prediction.***

Index Terms: ***Gabor filter, DWT, Gender prediction.***

I. INTRODUCTION

A human face has various information as gender, age, unique identity, and gesture. Computer vision analytics for extraction of these information from facial image can be utilized in varied applications as the field of biometric authentication and behavioral analysis. Facial gender recognition is used widely in human machine interviews; digital marketing, real time targeted advertisement and gender demographic analysis [1]. Mechanism of gender recognition have consecutive steps face ROI detection, image preprocessing on detected face, feature extraction, feature selection and optimization and classification as male or female. Image preprocessing step consist different algorithms of preparing image better for feature extraction as removing noise cropping, resizing, color format. Face detection step comprise pointing out face area in the image, take the face area from image and remove the rest of image. Feature extraction stage generate different features coefficients as color, texture or edge pattern and extract key component from it through feature selection. Selected feature can be optimized using feature optimization and finally given to classifier [2]. In the area of gender prediction, many technique has been evaluated but most of acceptable label accuracy in constraint environment. Performance of existing approach is varying due to rotation, illumination and variation in poses in terms of position orientation and size and expression. Varying age is also challenging problems of the facial gender identification due shape deformation of eyebrows, eye, mouth, skin. These challenges can be solved using optimized feature extraction [3]. Edge and texture feature provide the sufficient information for unique determination of the gender. histogram of gradient (HOG) [5], local binary pattern[6] and CNN provide the texture pattern of face while Gabor[4], DCT [7], scale invariant feature[8] etc provide the edge feature of face. Dimension of feature are reduced using dimensionality reduction and features are optimized using feature optimization approach. In existing state of art method have used Linear Discriminate Analysis (LDA) [10] Principal Component Analysis (PCA) [9] and pooling in deep based learning approach. In this paper, A study of gender recognition is carried out with problem identification in existing gabor filter based feature engineering for gender classification. In this research, it has found out the problem in existing state of art technique based on Gabor filter feature engineering model and provides the optimized solution for feature engineering. The proposed max-DWT can reduce the redundancy of Gabor egde-texture and enhance the unique feature relationship to class in order to increases accuracy system.

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II. PROPOSED MODEL

The proposed model for gender analysis from face is designed to classify gender class based on face of person. The proposed facial gender recognition model is described in details mythology as following.

A. Haar Cascaded Face Detection

Image is transformed into gray scale and haar features are extracted for detection of interested ROI as face. Haar features are given to cascaded adaboost classifier [11] with trained model which provide bounding rectangle on face in each given image and detected ROI rectangle is cropped from image.

B. Proposed Model of Edge Feature Extraction and Optimization

Gabor is 2D Gaussian sinusoidal coefficient matrix for a given orientation and wavelength defined as equation (1) [12,26].

$$Gk(a,b,\lambda,\Theta)=\frac{1}{2\pi\sigma_a\sigma_b}e^{\frac{-1}{2}\left(\frac{A_1{}^2}{\sigma_a^2}+\frac{B_1{}^2}{\sigma_b^2}\right)}e^{i\left(\frac{2\pi A}{\lambda}\right)} \qquad (1)$$

A_1 and B_1 is represented on orientation (θ) as defined in equation 2 [13].

$$\begin{cases} A_1 = a\cos\theta + b\sin\theta \\ B_1 = -a\sin\theta + b\cos\theta \end{cases} \qquad (2)$$

Gabor feature matrix $GM_{m,n}(i,j)$ is outcome of convolution operation of image I(i, j) and $Gk(a,b,\lambda,\Theta)$ as defined in below equation (3) [14].

$$GM_{m,n}(i,j)=I(i,j) * Gk(\lambda,\Theta)_{m,n} \qquad (3)$$

Gabor Features $GM_{m,n}$ have mn of size two dimension. I(i,j) is two dimensional space while scale Gabor filter generate 4-dimensional feature space. Here M and N_θ is number of scale and angle used for Gabor kernel respectively. Dimensionality reduce the performance and redundancy reduce the accuracy of system. Using extensive experiments we have used 3 different scale, 5 orientation {0,45,90,135,180}. The problem of redundancy and dimensionality reduce by optimization using proposed maxDWT technique.

C. Feature Optimization

Extracted Gabor features are optimized using proposed max feature optimization process in which feature coefficient is evaluated by maximum of all positional Gabor features coefficient as defined in equation (4) and it decreases Gabor matrix dimensions from 15 to 3. It avoids the redundant edges on eye, lips etc. in different orientation as shown in figure 1 and Gabor-max resultant coefficient matrix in figure 2. In our experiment, this approach reduce the dimensionality as well as redundancy.

$$GMax(i,j)=\max\{GM(i,j)_0,GM(i,j)_{45},GM(i,j)_{90},GM(i,j)_{135},GM(i,j)_{180}\} \qquad (4)$$

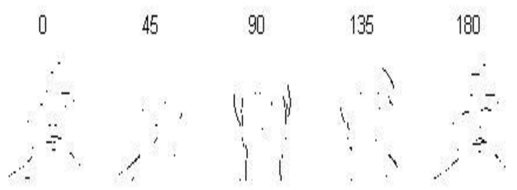

Figure 1: Different Gabor feature using 5 different orientations {0, 45, 90, 135, 180}. The redundant edge is shown at different location as lip, eye, eyebrows, nose and other facial points. Dimensional of Gabor feature also in 5 different matrix.

Figure 2: Feature after maximum operation on different Gabor orientation matrix which convert into single feature using proposed features extraction and resultant feature shows the reduced redundancy and dimensionality (5 Gabor orientation to single Gabor-max matrix).

D. Discrete *Wavelet Transform*

Discrete wavelet transform (DWT) [15,25] is used to convert the feature from spatial domain to frequency domain. DWT convert a given Gabor-max feature matrix to different four frequency range band (LL,LH,HL,HH) as shown in figure 3. Each band shows different characteristics of image in size (M/2*N/2) of Gabor-Max. LL band is generated by average value of neighbor coefficients and it presents all characteristics features of Gabor-max in reduce size of ¼ times. While HH represents the edge points. LL band is smoothing matrix of Gabor-max and it is extracted for further DWT operation. Finally LL band at level 2 is extracted for final features which reduce size by 1/16 of Gabor-max. The proposed Gabor-max-dwt process reduced the size of features from MxN into MxN/16 where M,N represents the height, width and number of orientation respectively.

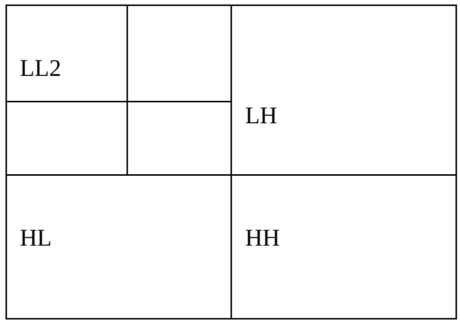

Figure 3: DWT approach of feature transform and decomposition at two levels.

E. Classification

Extracted feature of proposed Gabor-max-dwt is used to train the model using Naive bays classifier [17] with training data. The dataset is used challenging data as FERET dataset [16] which is divided into two group in training and testing with ratio of 80:20. The testing set is validated on trained network with K5 cross validation for gender recognition.

III. EXPERIMENTS, RESULTS & ANALYSIS

The Proposed feature engineering model of facial Gender classification is evaluated on widely used FERET dataset [18]. FERET has some of real time challenges as POSE variation, background variation, variability in hair style, illumination, orientation, age group, race, obstruction on face as ear rings, specks, nose pin and birth mark. All these challenges make hard to recognize facial gender classes correctly.

On the FERET data, following experiment is done. The data is divided in 5 equal disjoint subset and according 5 cross validation with training testing aspect ratio 80:20, the face is detected on each image and feature are evaluated using proposed engineering model. The NAIVE BAYS (NB) classification is used with linear kernel and 5 cross validation accuracy are evaluated after five iteration.

The proposed model of engineering provide 95% mean precision accuracy which is much better than existing approach of Gabor filter method and other state art of method presented in table 1. Existing approach provide as Gabor-PCA, Gabor-meanPCA provide accuracy 89% and 88.47%. Principle component analysis (PCA) decreases dimensionality of Gabor feature matrix but it does not reduce redundancy and not optimize the accuracy always While proposed approach of Gabor-max-DWT reduce the dimensionality as redundancy with feature optimization. Table 2 shows the confusion table in which class wise mean precision accuracy is also recorded for FERET dataset and results shows that female images are more confused than male. The second experiments is carried out as cross data validation in which model is trained using FERET dataset and testing is done on FACE94 data. This experiment shows results of mean accuracy of 90%. The faces captured through FERET have different variability which is used in training while testing of FACE94 have different characteristics as persons, background variation, age group, race, illumination variation, image quality, POSE variation etc. The above variability reduce the mean accuracy of validation data Face94 over FERET trained model.

Table 1: Comparison of results: Proposed technique v/s existing State of Art Results for gender recognition. Results show that proposed approach is much better than other state of art technique.

SN.	Feature Extraction Approach	Accuracy (%)
1	PCA-SVM[RBF] [20]	77.4
2	PCA - SVM [linear kernel] [20]	72.00
3	Gabor filter + PCA [19]	83.00
4	LBP – PCA [22]	86.5
5	Gabor-meanPCA [21]	88.9
6	Texture using LBP Neural Network [22]	86.5
7	Gabor-PCA- SVM [linear kernel] [23]	84.51
8	HOG SVM [24]	84.75
9	Gabor-meanPCA- SVM [linear kernel] [23]	88.47
10	Proposed Gabor-maxDWT –Naïve-Bayes with FERET data	95.00
11.	Proposed Gabor-maxDWT –Naïve Bayes with validation testing of Face94 data on trained model with FERET	90.00

Table 2: Confusion matrix : proposed Gabor-maxDWT for gender recognition

Gender	Male	Female
Male	96	04
Female	06	94

IV. CONCLUSION

In the proposed model of facial Gender analysis; face is detected and gabbro features is applied for feature extraction in which huge dominion gabbro matrix with redundant feature are generated. As par defined maximum value of respective positional is extracted among 5 different Gabor matrix and convert the 15 Gabor bank into 3 Gabor-max matrix. The extracted feature are further optimized using Discrete Wavelet triform in which coefficients are transform in different frequency component. DWT generate texture relationship of extracted feature in 4 frequency block. The LL block of DWT depicts the best texture relationship of extracted gabbro-max feature so it is extracted and remaining is discarded. This process reduce feature ¼.

This process of DWT feature extraction is applied again on extracted LL block. Dimensionality of Gabor-max feature matrix is suppressed by 1/16 using 2-level DWT. The five cross validation is applied on FERET dataset which achieved 95% accuracy. In the second experiment, the trained model with FERET dataset is tested with FACE94 dataset and 90% accuracy is achieved. The experimental results of proposed approach is compared with different existing state of art methods in Table 1 and it is derived that proposed approach is much better than existing approach as Gabor-PCA, Gabor-dwt and Gabor-LBP. The results shows that proposed technique achieved 95% correct recognition rate while existing Gabor-PCA, Gabor-meanPCA feature extraction claims 83%, 88.9% accuracy respectively. Gabor filter is a method of projection and generation the edge-texture pattern in image but increases the feature vector size. The model reduces the overall size of final feature vector and hence reduces the training and testing time also. Proposed Gabor-maxDWT Facial gender recognition reduces the confusion among classes due to reduction of redundancy and increases the performance of system due to reduction of dimension and feature vector size.

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