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AGE INVARIANT FACE RECOGNITION USING QUADRATIC SUPPORT VECTOR MACHINE – PRINCIPAL COMPONENT ANALYSIS

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Abstract

Age Invariant Face Recognition (AIFR) is a new research area in the domain of face recognition that lately received a lot of interest due to its tremendous potential with relevant applications in real-world. It is very challenging research problem to extract robust features describing aging facial information, usually when broad age difference between face images are perceived. In this paper, by using the quadratic support vector machine and principal component analysis technique of feature selection that is robust to aging we address this challenge and achieved the highest accuracy as compared to other methods such as K-Neighbor Neural Network (KNN), Probabilistic Neural Network (PNN), Backpropagation Neural Network (BPNN). FGNET aging dataset is used for the implementation of proposed method which includes a total of 82 separate subjects comprising 1002 images and each subject includes 6-18 images per subject obtained primarily from scanning photographs of subjects between the age ranging from newborn to 69-year-old subjects. From the images, LBP, Gabor and shape features have been extracted and PCA is used as a method of feature reduction. Four stages have been explored in this work: (a) Face recognition (b) Identify the gender of the object (c) Identify the age of the subject using the backpropagation neural network (BPNN) (d) Age invariant face recognition using KNN, PNN, NN and QSVM-PCA. The highest accuracy is achieved using the Quadratic Support Vector Machine – Principal Component Analysis (QSVM-PCA) classifier.

Keywords:

Age Invariant Face Recognition, Facial Aging, QSVM, Databases

1. INTRODUCTION

Age invariant face recognition (AIFR) has been a major research area in the domain of computer vision from the last ten years [1]. Face age recognition is a popular field for study, primarily due to growing security demands and its possible applications for commercial and law enforcement applications. AIFR can be used to recognize the face with age differences [1]-[4]. In many applications, AIFR performs significant role such as biometric authentication, border control, forensic applications, and tracking and identification of missing person etc. With a different age pattern per person, facial characteristics gradually changes with the passage of time, and recognition of a person with age invariant feature has become a challenging and important field for researchers [4]-[7]. The effects of aging on a particular subject depend on individual genes, personal health, lifestyle, etc. It is a challenging research problem to extract robust features describing aging facial information, particularly when broad age differences among facial images are perceived [7]-[12].

Datasets (Table.1) perform a fundamental analytical role in testing facial recognition algorithms. Several facial datasets are presented, apart from them only some are particularly established to be used in the AIFR. The issues can be described as follows in these datasets (a) few images at different ages (b) blur effect or image distance from the camera (c) limited number of training images and (d) hard to recognize small age person's image. Since the human face undergoes various changes over time, the age-invariant features of the human face are difficult to determine. Recognition of the same person at different ages is required in many security applications such as to avoid that the same person issued many government documents (e.g. passport, identification certificate, and license) containing face image. Rate/speed of recognition is also important in real-time applications which can be improved by using types of features extracted and the number of features selected from the extracted features. Extracted features are correlated to each other and correlated features do not offend useful in the characterization problem. Hence, the entire features set are selected using a feature selecting method which removes correlated component and obtained underlying uncorrelated feature set.

PCA simply assumes that the largest variance or spreads as the most interesting function. The dimension with the greatest variance corresponds to the dimension with the greatest entropy and encodes the maximum information. The smaller eigenvectors often simply represent components of noise, while the larger eigenvectors often correspond to the key components defining the data selection. Dimensionality reduction using PCA is then done simply by projecting the data onto the covariance matrix's largest eigenvectors.

In this work, we provide a complete solution for an effective AIFR in various applications, such as biometric authentication, passport authentication, cybercrime, finding the missing person, etc. as compared to other biometric system based on fingerprint or iris, this is also a non-contact system. In this work, four stages have been explored: (a) Face recognition (b) identify the gender in the image (c) identify the age in the images using backpropagation neural network (BPNN) (d) age invariant face recognition using K-Neighbor Neural Network (KNN), Probabilistic Neural Network (PNN), Neural Network (NN) and Quadratic Support Vector Machine – Principal Component Analysis (QSVM-PCA). In this work, the database is subdivided into training and testing to calculate the performance parameter. In this work texture feature named the local binary pattern (LBP) and Gabor with shape features are extracted for recognition of age [12]-[18].

2. RELATED WORK

Park et al. [1] proposes 3G aging method to enhance the face recognition accuracy by compensating the variations in age. 3D face models are used by converting 2D face images into 3D because it gives more accurate modelling capability. This method is capable to manage both growth and adult face aging effects.

Li et al. [2] proposes discriminative model for age invariant face recognition. Without depending upon the generative aging model this model approaches the face aging issue in more straight forward manner. Many LDA-based classification algorithms are built using random sampling of the training data and feature space, and then coupled using a fusion rule to produce a robust conclusion.

Gong et al. [3] proposed a novel hidden factor analysis (HFA) approach to address the complex challenges of age invariant face recognition which uses identity factor component and age factor component from the facial image of person. HFA reduces the variation caused by these two factors by using probabilistic model.

Li et al. [4] presents maximum entropy feature descriptor (MEFD) technique to solve the matching and representation problems in Age invariant face recognition. Face recognition performance can be improved by maximizing the code entropy. Simultaneously Identity factor analysis (IFA) method is presented to enhance the recognition accuracy.

Xu et al. [5] proposed coupled auto-encoder networks (CAN) to tackle the age invariant face recognition and retrieving issues. CAN is a system that combines two auto-encoders with two shallow neural networks to suit complex nonlinear ageing and de-aging processes.

Gong et al. [6] suggested a model named latent factor guided convolution neural network (LF-CNN). To address the analysis of Convolution neural network (CNN) parameters Latent identity analysis (LIA) method is established. This model derives the age invariant deep features by understanding the CNN parameters, necessary for the Age invariant face recognition task.

It is observed from Table.1, few algorithms has been investigated on AIFR. It is also recorded that accuracy of the previous work need to improve with efficient algorithm.

Table.1. Summary of accuracy rate on FG-NET dataset

Method used	**Subject/ Images**	**Accuracy (%)**
3G aging model [1]	82/1002	37.40
Discriminative analysis method with densely sampled descriptor [2]		47.50
Hidden factor analysis [3]		69
Maximum entropy feature descriptor [4]		76.2
Coupled auto encoder network [5]		86.5
Latent factor guided convolution neural network [6]		88.1

3. WORKFLOW ADOPTED FOR AGE INVARIANT FACE RECOGNITION

The workflow adopted for AIFR system as shown in Fig.1.

3.1 DATASET

The FG-NET aging data contains a total of 82 separate subjects (6-18images per subjects), including 1002 images collected mainly scanned images of subjects aged up to 69 years [1]-[6], [10]-[20]. In this database, the age difference is between 0-45 years. Gender and facial expression may have negative effects, among several factors influencing accuracy of system. In this work, the benchmark databases FGNET is used for age-invariant face recognition [10]. FGNET sample images are shown in Fig.2.

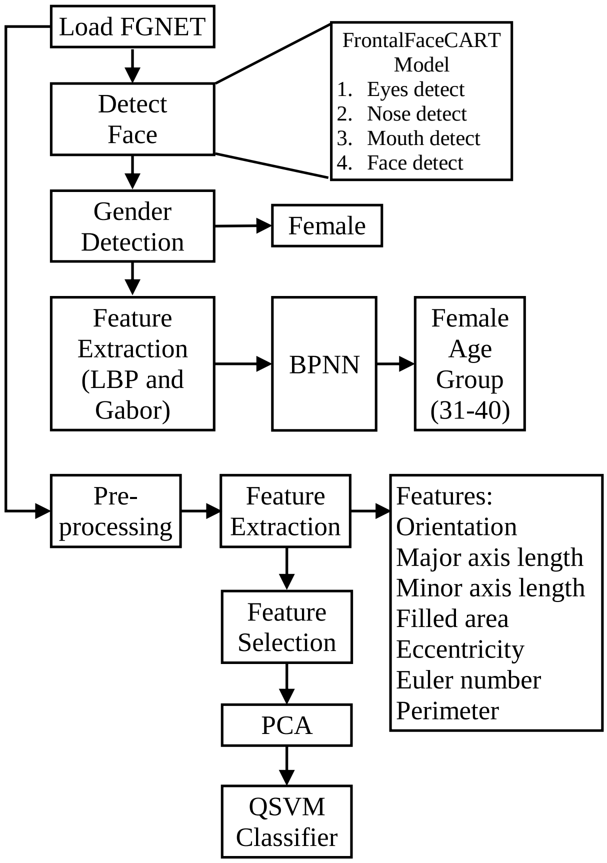


Fig.1. Workflow adopted for AIFR system

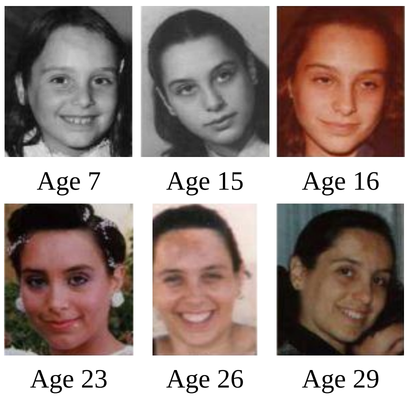


Fig.2. Example of images from FGNET Database

4. PRE-PROCESSING

Pre-processing of the images is also an essential step in further analysis. The pre-processing stage for preparing an image for the algorithm for classification is shown in Fig.3

The pre-processing having four basic steps (i) cropping (ii) resizing (iii) histogram equalization and (iv) normalization.

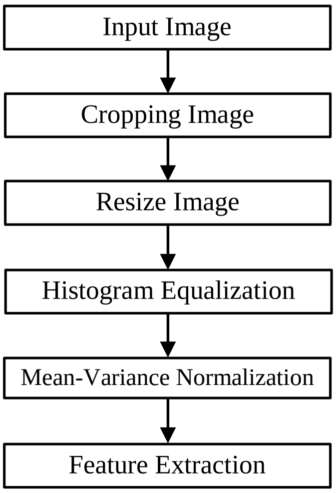
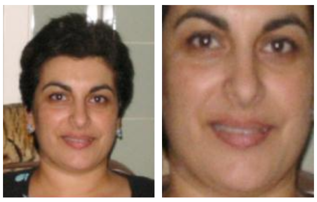


Fig.3. Pre-processing of image

4.1 CROPPING OF IMAGE

The background of the picture and some parts of the face, including hair and collar, is the entity that affects the accuracy of the image. This object should therefore be removed from the main picture, so that system accuracy can be increased. Cropped image decreases the size of the image and increases the speed due to the removal of vast part from image. The Fig.4 shows the original image and the cropped image.



(a) (b)

Fig.4. Cropping of image (a) original (b) cropped image

4.2 RESIZING OF IMAGE

The size of the image is different in the dataset so the size of the image also adjusts as 128×128.

4.3 HISTOGRAM EQUALIZATION AND NORMALIZATION

The method of Histogram equalization (HE) is used to distribute their intensity levels. In terms of an image histogram, HE increases the intensity range and expands the intensity distribution more than flattened peaks and valleys. This technique increases the areas of low contrast without decreasing the overall contrast of the image. In this work, histogram equalization was used to adjust the contrast of the dataset.

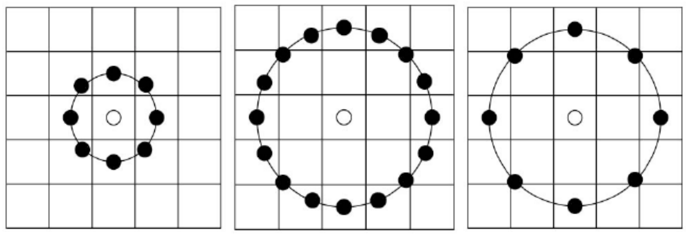
The technique for Mean or Variance Normalization (MVN) is commonly used to make recognition features more stable. Standardization techniques of features can mitigate to a large extent the inherent disparity between training and testing environments. Both mean-variance normalization (MVN) and histogram equalization (HE) is used for feature vector analysis to substantially enhance the classification.

5. FEATURE EXTRACTION AND SELECTION

From the images, LBP, Gabor and shape features have been extracted and PCA is used as a method of feature reduction.

5.1 LBP FEATURES

For texture classification, LBP is important feature which codifies the local primitives (curved edges, lines, flat areas, etc) into a histogram function. Ahonen's proposed LBP-based face in 2006 and the definition stated that the images are separated into local regions, and LBP texture descriptors are extracted separately from each region [4] [6].



(a) (b) (c)

Fig.5. Neighbourhood (a) p=8, r=1 (b) p=16, r=2 (c) p=8, r=2

5.2 GABOR FEATURES

In age-face image analysis and processing, the Gabor features have been used extensively. In general it is used for texture analysis, which essentially means that it analysis whether there is any particular frequency material in the image in specific directions or region of analysis in a localized field [1] [3] [5]. The Gabor feature as shown in the Fig.6.

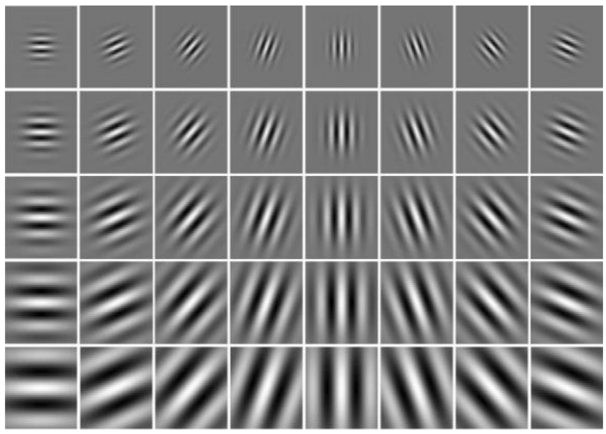


Fig.6. Sample images of Gabor feature

5.3 SHAPE FEATURES

The shape features as solidity, area ratio, Euler number, convexity, Elliptic variance, Eccentricity, Circularity ratio, Rectangularity, are extracted from the images.

5.4 FEATURE SELECTION USING PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA simply assumes that the one with the largest variance or spread is the most interesting function. This statement is based on a theoretical point of view of information, since the dimension with the greatest variance corresponds to the dimension with the greatest entropy and therefore encodes the most information. The smallest eigenvectors often simply represent components of noise, while the largest eigenvectors often correspond to the key components defining the data. Dimensionality reduction by using PCA is then done simply by projecting the data onto the covariance matrix's largest eigenvectors.

5.5 TRAINING AND TESTING OF FG-NET DATABASE

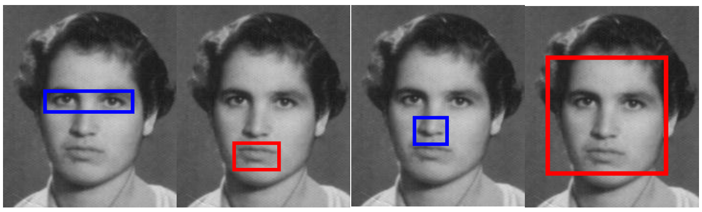
The FGNET database includes 1,002 face images from 82 different people [1]-[6], [10]-[20]. The age of the person range from 0 to 69 years. The average number of existing face images for each person is approximately 12. The age gap in this database is 0-45 years. 80% of the dataset images are chosen randomly to obtain training features and 20% are for testing purpose.

6. RESULT AND DISCUSSION

There are three different steps to recognize the age invariant face recognition system for FGNET dataset. The steps are as follow:

Step 1: Identification of parts of face

From the Fig.7, it is observed that parts of the face are most important for further analysis. Shape and size of face part decide the age of the person.



(a) (b) (c) (d)

Fig.7. Detection of parts of the face for further analysis (a) Eyes Detection (b) Mouth Detection (c) Nose Detection (d) Face Detection

Step 2: Find Age and Gender of the person

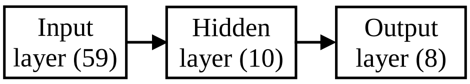
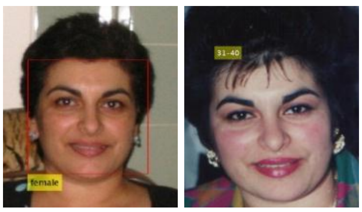


Fig.8. Neural network training for identification of age and gender of person



(a) (b)

Fig.9. Test images after training (a) gender and (b) age of person

A total of 59 features are extracted from the database based on texture and shape of the image, 10 hidden layers are further processing. In this work LBP and Gabor feature are extracted from the data base. Neural network are used for the identification for age and gender of person. From Fig.8, train the network using BPNN with 10 hidden layer and 8 classes.

The backpropagation neural network algorithm train the network and all persons age divide into 8 categories. The performance of the BPNN as shown in Fig.9-Fig.11.

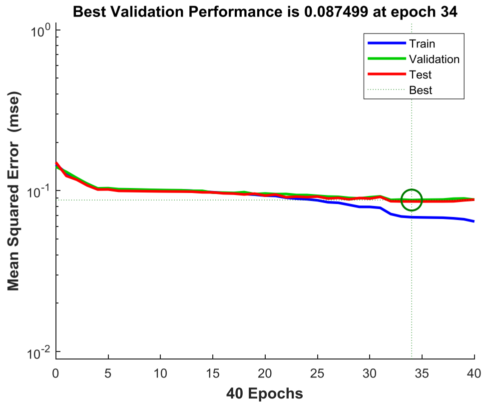


Fig.10. Performance of BPNN algorithm

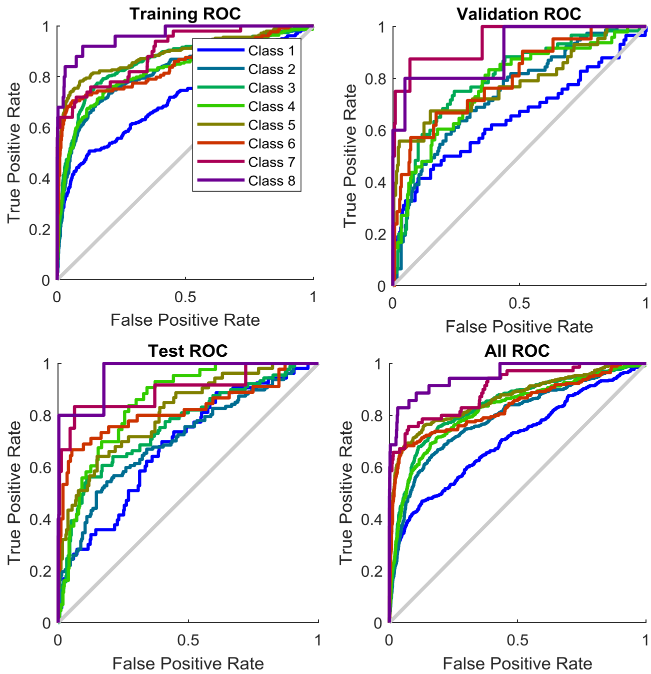


Fig.11. ROC Curve of BPNN algorithm (Training, Test, Validation)

It is observed that the age of the person divides into 8 classes. The accuracy of the BPNN algorithm is 90.67%.

Step 3: Feature selection using PCA and QSVM classifier

In this work, BPNN does not provide accurate results in terms of accuracy so that a PCA is used as a feature selection method. It reduced the feature vector into an uncorrelated feature set. QSVM is a benchmark classifier which decreases the false positive rate and increases the true positive rate and improves accuracy of system. The ROC curve using QSVM-PCA shown in Fig.12, False positive rate curve using QSVM-PCA shown in Fig.13, and True positive rate curve using QSVM-PCA as shown in Fig.14 respectively.

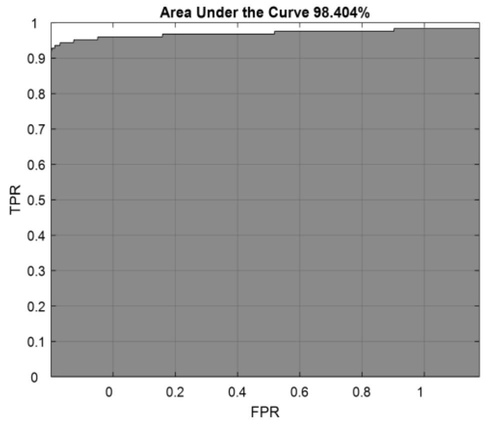


Fig.12. ROC curve using QSVM-PCA

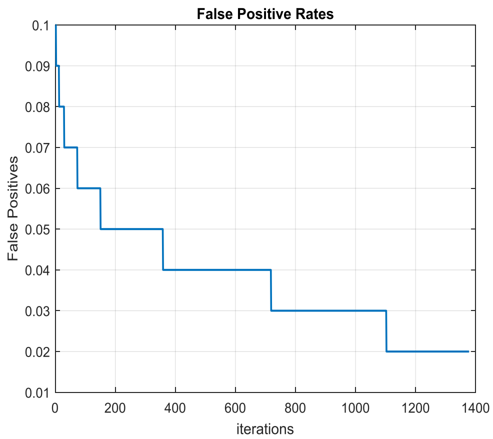


Fig.13. False positive rate curve using QSVM-PCA

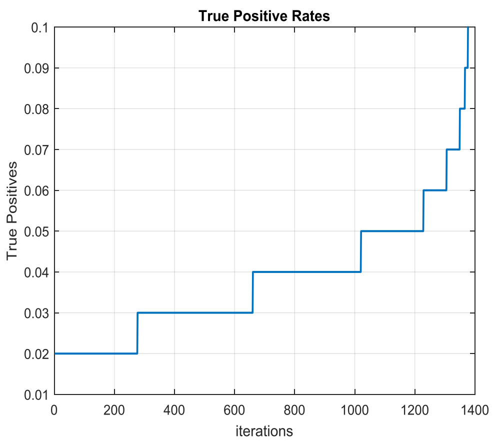


Fig.14. True positive rate curve using QSVM-PCA

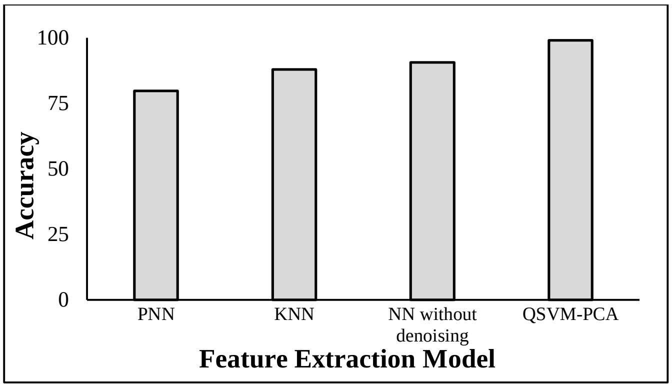


Fig.15. Comparison of previous work with proposed QSVM-PCA method

7. CONCLUSION

Face recognition has applications in many machine vision fields, such as law enforcement and forensic investigation, homeland security, missing persons, and checking the passport and visa. In these applications, the images in the database may not be updated continuously. As aging slowly leads to changing the important features of the face image, it directly affects the performance of face recognition approaches. Hence, it is necessary to consider the aging variations in face recognition. In this paper, some AIFR approaches have been implemented. Also, the results of these methods have been compared to previous work. These results show that age-invariant face recognition approaches which consider both component-based representation of facial images and identity factors have better performance compared with the other face recognition methods across aging. It is concluded the aging effect identification using QSVM and PCA feature reduction method achieve 99% accuracy.

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