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Age Invariant Face Recognition Using Artificial Neural Network

M. J. Raval[1], Shankar Parmar[2]
[1]PG Student,[2] Asst. Prof.,
Department of Electronices & Communication
G H Patel College of Engg. & Technology, V.V.Nagar

Abstract: *In current research, face recognition technology is being used to improve human efficiency when recognizing faces, is one of the fastest growing fields in the biometric industry. The challenges in developing age invariant face recognition are large intra-subject variations and large inter-user similarity. The main intra-subject variations are (pose, illumination, expression, and aging) commonly encountered in face recognition. In this paper, feature extraction based age invariant face recognition framework is modelled. In this system first component or features are extracted using two local feature extraction SIFT (scale invariant feature extraction scheme) and MLBP (multi-scale local binary pattern) methods. This feature vector is then classified using artificial neural network. These results are normalized and using score sum fusion rule recognition in performs. Evaluation of this system is done by different measuring parameters to check the robustness of the proposed system. Experimental results shows that the accuracy is increased up to 53% compared to existing approach.*

Keywords- **Age invariance, SIFT, MLBP, ANN, Face Recognition.**

I. INTRODUCTION

Automatic face recognition is an important yet challenging problem. This challenge can be attributed to (i) large intra-subject variations and (ii) large inter-user similarity. Among these variations, aging variation is now beginning to receive increasing attention in the face recognition community. Designing an age-invariant face recognition method is necessary in many applications, particularly those that require checking whether the same person has been issued multiple government documents (e.g., passports and driver license) that include facial images.
Narayanan Ramanathan et al. [4] has introduced Bayesian age difference classifier that classifies face images of individuals based on age differences and performs face verification across age progression. In this method author only determined the age difference of two images that are given to the Bayesian classifier. Xin Geng et al. [2] has introduced the AGES pattern based age invariant face recognition. The basic idea is to model the aging pattern, which is defined as the sequence of a particular individual's face images sorted in time order, by constructing a representative subspace. The current preprocess does not retain the information about the outer contour size of the face. However, face size varies across ages, especially during formative years.

Unsang Park et al. [3] has introduced 3D aging modeling. They have suggested a 3D facial aging model and simulation technique. The shape modeling from 2D to 3D field for compensate for pose invariance and, illumination invariance. aging simulation results in terms of face recognition performance can further improve simulated aging. Anil k jain et al. [1] has introduced the local feature extraction and matching framework. They have used SIFT and MLBP as feature extraction scheme and MFDA for matching.

The paper has been fragmented into six parts. Section 2 discusses the tongue anatomical pre-cancerous diseases and its related problems. Section 3 comprises of the basic concepts of leukoplakia, extraction, its detection and further details. In section 4 we propose an approach for detection of leukoplakia. Section 5 concludes the paper. Acknowledgments are being provided to specialized dental doctors, without their massive support nothing would have been possible in section 6.

II. Problem Definition

Different approaches are being employed to achieve age invariant face recognition. These approaches are for either age simulation or age estimation. A suitable feature demonstration and an efficient recognition structure for age invariant face recognition leftovers a remaining task. It is a very challenging task and difficult to find a generalized approach. Our aim is to achieve higher efficiency using a different classifier.

III. PROPOSED APPROACH

Our proposed approach consists of two components: local feature representation and classifier for matching. We describe each component of the approach in the following subsections.

TABLE I: PROPOSED ALGORITHM

Steps	
1	Acquire face images from FG-NET database.
2	Resize the image in 150x200 pixels.
3	Convert RGB image into gray scale.
4	Divide image into 16x16 and 32x32 sized patches
5	Extraction of local features on each patch.
6	Classify these features using artificial neural network.

A. Image Acquisition

We have used FG-NET database developed by the Face and Gesture Recognition Research Network. And it is publicly available. The FGNET database consist 1,002 face images of 82 different subjects. Among 82 subjects 48 are males and 34 are females faces and the age ranges from 0 to 69 with different variations like illumination, pose, expression, beards, moustaches, spectacles, hats.

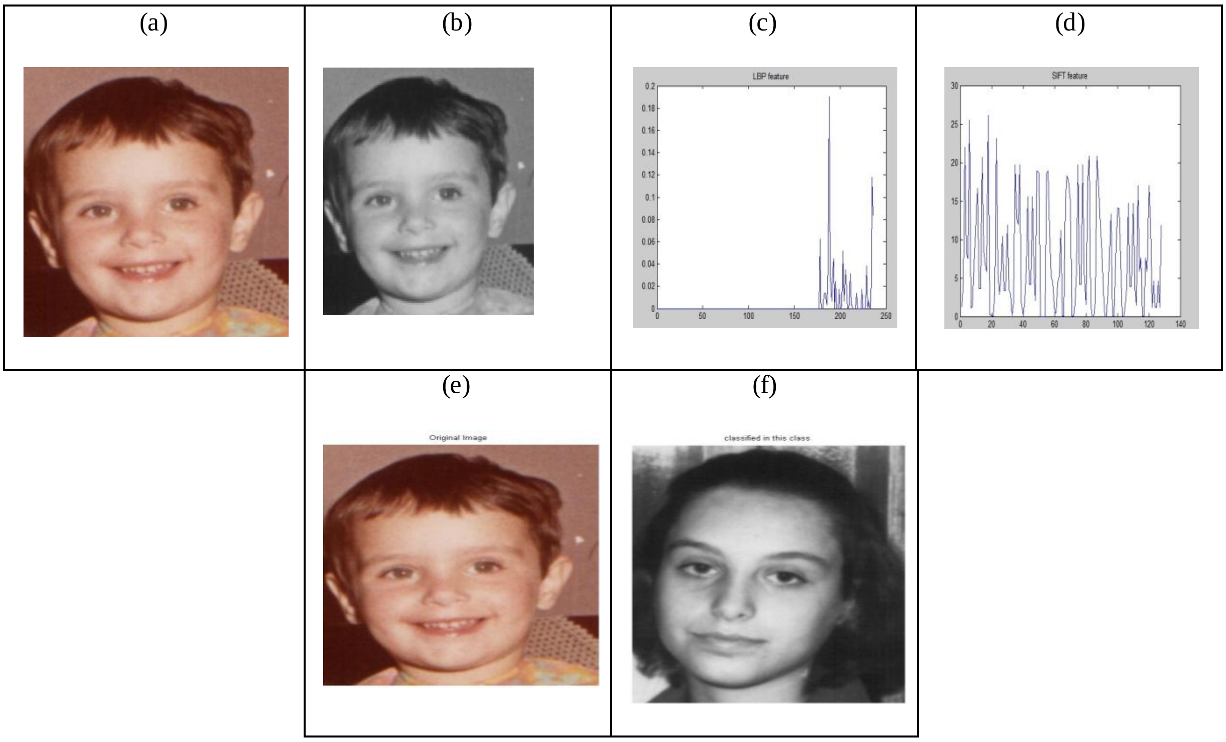


Figure 1: (a) Original Image (b)resized image 150x200(c) MLBP feature vector (d) SIFT feature vector (e) query image (f) output image

B. Pre-processing steps

In pre-processing steps we have original image in form of RGB and converted it into gray-scale image. After that we have normalized to 150 by 200 pixels. And then divided into 88 overlapping patches for each has patch size of 32 by 32 or 408 overlapping patches for patch size of 16 by16. On each patch we have extracted features.

C. Feature Extraction

The general definition of feature is that it is specific structure in image like point, edge or object. In machine learning a feature is an individual measurable property of a phenomenon being observed. Features are usually numeric, but structural features such as strings and graphs are used in syntactic pattern recognition.

The extraction of features means selection of such content who overcome the curse of memory consumption and unneeded raw image data as capture from cameras would be excessively slow and compound to process by most complicated algorithm.

In this paper we have used two local feature extraction schemes SIFT (scale invariant feature transform) and MLBP (multi scale local binary pattern). Purpose of using these two feature extraction schemes is SIFT are invariant to rotation, scaling, translation and small distortion and MLBP are invariant to monotonic change in gray-scale also fast to calculate and complementary for some disadvantage of SIFT feature

SIFT (scale invariant feature transform)

1. **Scale-space extrema detection:** The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.
2. **Keypoint localization**: At each candidate location, a detailed model is fit to determine location and scale. Keypoints are selected based on measures of their stability.
3. **Orientation assignment:** One or more orientations are assigned to each keypoint location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.
4. **Keypoint descriptor:** The local image gradients are measured at the selected scale in the region around each keypoint. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination. This approach has been named the Scale Invariant Feature Transform (SIFT), as it transform

MLBP (Multi-Scale Local Binary Pattern)

The basic local binary pattern operator mechanism in a 3 × 3 pixel block of an image. The pixels in this segment are threshold by core pixel value, multiply by power of two and then added to get a label for center pixel. As region has 8 pixels so total $2^8=256$ different label can be obtain depending on the gray value of middle pixel.

MLBP is very robust in terms of gray scale variations, since the operator is by definition invariant against any monotonic transformation of the gray scale. MLBP is extension of the local binary patterns (LBP).

The limitation of original LBP is that it has small spatial area. In some texture due to 3x3 small block size the basic LBP operator is failed to capture large-scale structures. Nevertheless, the operator is not very robust against local changes in the texture, caused, for example, by varying viewpoints or illumination directions.

The straight way to increase the spatial support area to combine the information provided by N LBP operators with varying P and R values. By doing, this each pixel in image gets N different LBP codes.

D. Dimensionality Reduction

After finding features the dimensionality of the feature vector is high so we have used PCA (Principle Component Analysis) for that each SIFT or MLBP feature vector, break it into slices with feature from the patches of the same row in the image as one slice that way we have created 70 slices for each image. On each slice we have applied PCA for dimensionality reduction.

E. Classifier

The knoll of example acknowledgment has extensive differences of reasonable, therapeutic and modern applications. A portion of the numerous applications incorporate penmanship acknowledgment, clamor arrangement, and face acknowledgment, unique mark acknowledgment, and biomedical picture preparing applications, mammography, discourse recognizers, and so forth. With such a wide mixture of uses it is impractical to concoct a solitary classifier that can produce great results in all the cases. Thus, the classifier(s) received are profoundly subject to the issue space.

In this paper we have described artificial neural network as classifier. We have used supervised learning for our classification. The simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is given by Dr. Robert Hecht-Nielsen. He is the inventor of one of the first neurocomputers. According to him the neural network is defined as “a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.”

ANNs are processing devices it can be either software or real hardware that are generate after the neuronal structure of cerebral cortex of human brain but on minor scale. Neural networks are interconnected layers. These layers are made up of numbers of consistent nodes which called neurons. These neurons contain activation function.

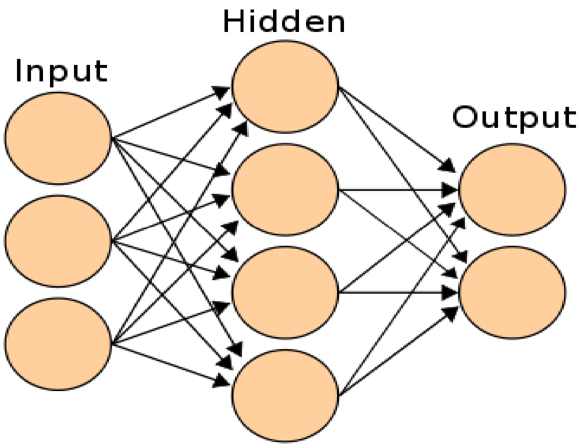


Figure 2: Artificial Neural Network

It has three sections first in input layer second is output layer and in-between this two layers several hidden layers are there for communication between input and output layers. Most neural networks have a number of ‘learning rule' which modify the weights of the links between layers in accordance with the input patterns.

F. RESULTS AND DISCUSSION

While there are some publicly available face datasets such as FERET [22], FGRC [21] and LFW [8] created and released for the face recognition research, only a few of them have addressed the aging problem until some recent attempts on age invariant face recognition.
In this section, we evaluate our proposed method by conducting age invariant face recognition experiments on the widely used FG-NET face databases. The following describes the details of the experiment setups and results.

1. Training stage

- In first step the both feature vectors SIFT and MLBP are divided into 70 slices with patches of the same row of image as one slice. On each slice calculate PCA.
- In each projected subspace we construct four neural classifier for each slice.
- The above procedure is repeat on 150 images of 20 different person. And the data is stored in a database

2. Testing stage

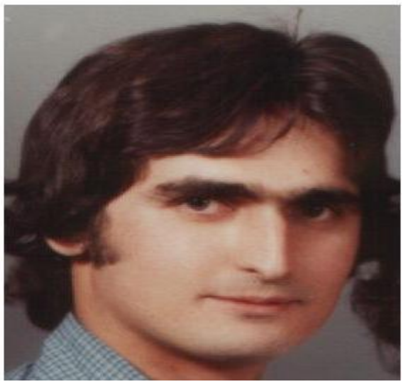
- On each testing image obtain 70 slices same as done in training stage
- For matching query image to gallery use the previously trained classifier
- For making final decision first of all normalized the output of classifiers and after that combine it using score-sum base fusion rule.

Original Image

classified in this class

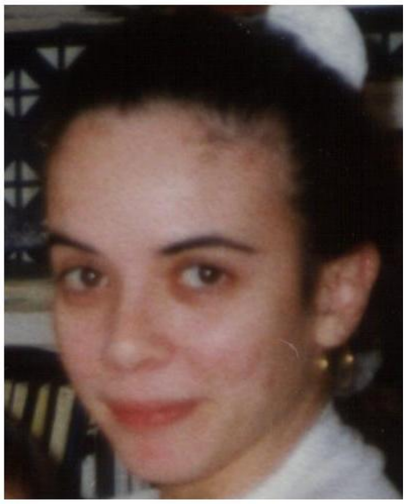
Original Image

classified in this class



Original Image

classified in this class



Measuring parameters

1) Precision

Precision or positive predictive value is the fraction of retrieved instances that are relevant. It can be calculate using following equation. It is proportion of the true positive against all positive results. It is also defined as measure of the accuracy provided that a specific class has been predicted.

$$precision \ = \frac{tp}{tp + fp}$$

Where

- tp= **true positive**. That means the number of faces correctly labeled as belonging to the positive class.
- Fp= **false positive**. It means the number of face correctly rejected.

2) Recall

Recall or sensitivity is the fraction of relevant instances that are retrieved. Calculated using below equation..it is also defined ability of a classifier to select instances of a certain class from a data set. It is commonly also called sensitivity, and corresponds to the true positive rate.

$$recall \ = \frac{tp}{tp + fn}$$

Where

- fn= **false negative** test result is one that does not detect the condition when the condition is present

3) Accuracy

Accuracy is statistical parameter to evaluate the performance of the classification system. It is the proportion of true results from the total number of examined sample. In classification terms Accuracy is the sum of correct classifications divided by the total number of classifications.

Table 1 Measuring Parameters

With database of 100 images of 20 classes	precision	recall	accuracy
In percentage	0.6315	0.36	53

4) Confusion matrix

To measure performance of the classifier we need to check the ability to correctly predict the classes. The confusion matrix shows the prediction made by classification model. Value represented by this matrix is the number of prediction made with the class corresponding to the column for example with correct value as represented by the row. Diagonal element shows numbers of correct classification for each class off diagonal elements shows the errors.

C =

3	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
0	4	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1
0	0	4	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
0	1	1	3	0	0	0	0	0	0	0	0	0	1	0	1	0	0
1	0	0	0	4	0	0	1	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	4	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	3	0
0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	3	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3: confusion matrix

5) CMC (cumulative match characteristic)

It is plot of the probability of identification against the rank. It shows the probability that a given user appears in different sized candidate lists. The faster the CMC curve approaches 1, indicating that the user always appears in the candidate list of specified size, the better the matching algorithm.

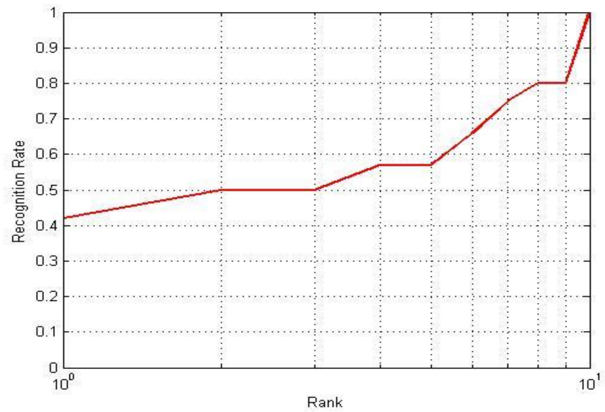


Figure 4: CMC curve

IV. CONCLUSION

The age invariant face recognition is most challenging area of pattern recognition. it has gain great deal of attention over a last few years. Existing work has only presented the age estimation and simulation. The presented work represents the feature extraction and matching structure for age invariant face recognition. feature extraction is done using two local descriptor SIFT and MLBP. And for classification we have used artificial neural network. Using this approach we reached up to 53% accuracy. For future work, proposed algorithm can be extended using other fast feature extraction scheme and for better performance robust pose invariant and illumination invariant algorithm. In presented work we have not considered the images with occlusion so in future it can be accomplished.

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