A New Multi Fractal Dimension Method for Face Recognition with Fewer Features under Expression Variations

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Abstract- In this work, a new method is presented as a mingle of Principal Component Analysis (PCA) and Multi-Fractal Dimension analysis (MFD) for feature extraction. Proposed method makes use of best decision taken from both the methods and make use of fewer and effective features than traditional algorithms without compromise in recognition accuracy. In order to ease the pre-processing we controlled the variance in each mode. It is done to train the system to understand and recognize facial variance present in image. Experiments with different datasets show that proposed method is more suitable for larger dataset, with higher efficiency.

Keywords: Multi Fractal Dimension, Principal Component Analysis, Intensity based fractal dimension, Fractal, K- Nearest Neighbour, Box Counting method.

I. Introduction

Face recognition, in previous ten years, has come up as popular research field in the computer vision using image analysis or processing. We can identify thousands of faces seen throughout our whole life and identify known faces at a glance though after year of separation. So we need such type of computational system model that can identify faces as human identify. Several algorithms have been introduced and renovated to achieve higher recognition rate based on their own points of strength and restrictions, but still many challenges remains to improve the efficiency or accuracy of their systems under different situations like illumination, pose and image resolution.

From last three decades many appearance based face recognition approaches have been proposed like Eigenfaces based principal component analysis (PCA), given by Turk and Pentlands [2]. Main idea behind the use of PCA was to reduce those dimensions which are non-repetitive in the image dataset i.e., with low Eigen values. ICA [4] was developed based on kernel Hilbert space, to work with non-Gaussian nature of the face images. Kernel based PCA [4] was introduced to enhance recognition speed

In this work we have extracted a scale and rotation independent feature Intensity Level-based Multi-fractal Dimension (ILMFD) and principal component based feature to get the higher efficiency. As ILMFD is basically an aggregate-image based feature, that captures the rough shape and texture of 3D-aggregates in its 2D projected form. After getting the feature, we are taking the final decision for recognise the face with the help of classifier according to best feature extracted from methods.

II. PRINCIPAL COMPONENT ANALYSIS

PCA method was first used as method of feature selection based on Eigenfaces[2]. Eigenfaces is projection of input images into that subspace where principal components appear orthogonal to each other. PCA was designed under unsupervised learning model to perform its feature selection. Suppose the training images have '*M*' number of images F_i with size $m\times n$. Algorithm grounded on PCA is described as below:

1. Reshaping of F_i into a column matrix with size of mn×1 in order to forma 2D matrix of size mn×M. As for an i^{th} image

2. Obtain the mean image of reshaped image matrix as

3. Centre the images by making difference between reshaped input image and as

4. Construct the covariance matrix

5. Do Eigen Decomposition on covariance matrix C. Let X a matrix that contains the selected eigenvectors based on the largest n Eigenvalues, where the X can be imagined as

   X = [x1 …………xn]

6. Project the testing sample into the acquired subspace to find the features which will forwarded for classification as

7. Test the classifier with features obtained in Yi

IV. MULTI FRACTAL DIMENSION (MFD) BASED ANALYSIS

Fractal:

Fractal is a geometric (fragmented) or rough shape that may be split in many parts, that part is (at least approximately) a minimized-size or reduced size copy of whole, this property of shape called self similarity and these shape has non- integer dimension.

We cannot say all self similar units are fractals, for i.e., a real line (straight lines) is seems self-similar but not pass for, remaining fractal shape characteristics, as, it is much regular to defined in Euclidian dimension terms.

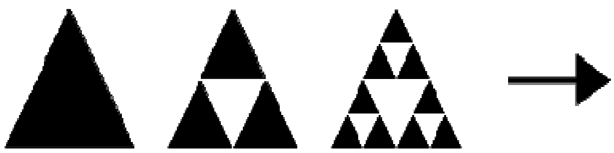

Figure 1: Sierpinksi triangle showing the self similarity.

Fractal dimension:

Fractal dimension in geometrical dimension which can be represent by D is a quantity which indicates of how a fractal shape used to fill space, as zooms down to get or achieved finer and finer scales.

Fractal dimension of the any structure or curve can be explained like to fit a line in one dimension is too big object, but in two dimension too thin object. Its dimension could be given in a sense of fractal dimension, which is nothing but a no. between one and two [13][14].

Lets we takes an object with linear size is 1 residing in dimension D, and reduced its linear size of the factor 1 / l in every direction of the shape, it takes $N = l^D$ number of similar shape objects to cover a original object. However, the dimension can be defined as follows given,

$$D = \frac{\log N(l)}{\log l}$$

1	2^1	3^1
2	2^2	3^2
3	2^3	3^3
D	2^D	3^D

No of copies made by scaling(N)αl^D

Figure 2: Analyzing the fractal dimension for different objects and fractal objects.

A fractal feature can be calculated in following step,

- First convert RGB image into gray scale one.
- Now from gray scale one, obtained n number of binary image by dividing the image at different intensity level.
- For each binary image count the no of occupied cell that occupied by those pixels that have intensity value in a particular range, from the help of box counting technique for different scale.
- By this we will get m different no of counts for m scales for binary image.
- Then using the following equation for finding the other parameters,

$$\text{Log}(M) = D \log(L) + C$$

Where, M is no of box used to count occupied cell in image, L is a size of scale, D is the fractal dimension for the images and C is a constant

- After m different values for L and M we will get D and C, these are the multi fractal parameters.

Box Counting Method:

Moving the box to the whole image, if box found one or more than one cell occupied, then corresponding cell in reduced scale image marked like occupied and count occupied cell in image.

From the following figure we can calculate the fractal with help of box counting method.
By different size of boxes we are getting different fractal dimension.

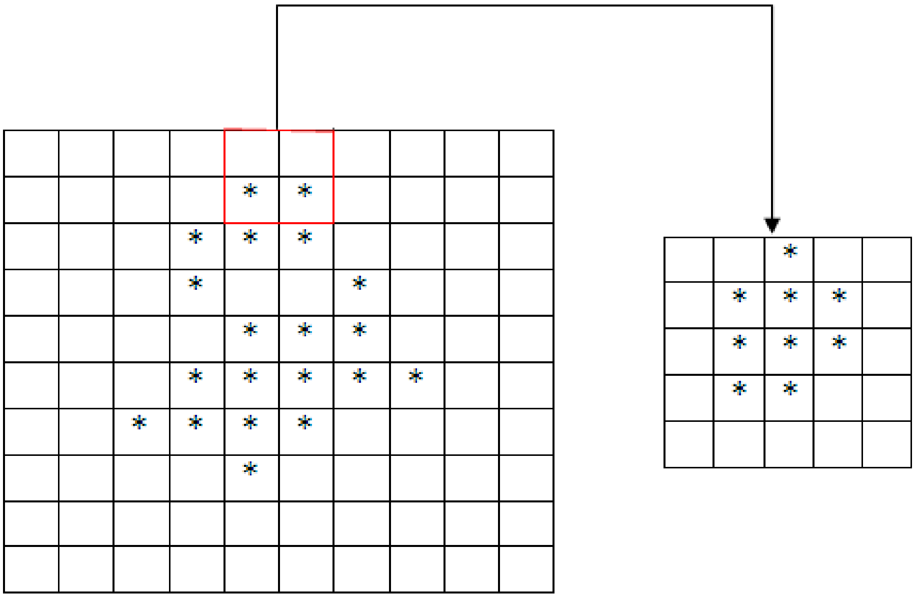

Figure 3: Counting the no of box used to cover the whole object.

Classification:

After the feature parameters are obtained from multiple sources the classifiers are made which takes these feature parameters as input and then classify the test image into one of the desired output classes. To understand the roll of classifiers on the features based on the proposed method we tested it with the neighbourhood classification approach that is k-Nearest Neighbour classifier.

V. PROPOSED WORK & IMPLEMENTATION

Based on above observation we are introducing our proposed method in which features extracted from the different features extraction methods are the inputs for the classification. The method has been presented below with the proposed modifications.

1. First we need to collect the face image database.
2. Obtain feature based on PCA and Intensity based Multi Fractal Dimension (MFD) feature.
3. Use the classifier for the classification purpose and get the decision against feature extraction methods.
4. With the help of combining or clustering protocols we are taking the final decision of face recognition**.**

Architecture:

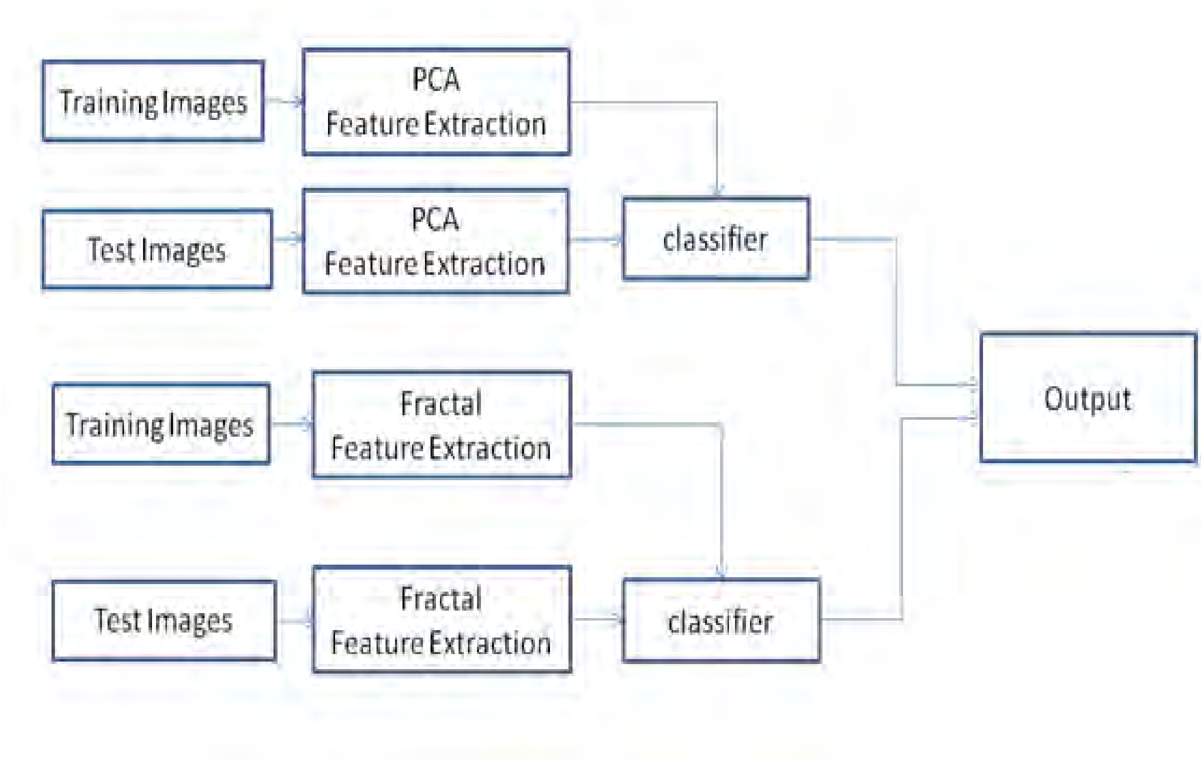

Figure 4: Architecture of Proposed system

As we can figure out with the architecture first we are dividing the database into set of training images and testing set for experiment purpose. And then with the help of feature extraction method, extracting the features for training set images and testing set object. Then comparing these testing images of faces with the dataset or extracted feature or training and giving the decision a particular face belong to which class with the help of classifier. But the final decision which we are giving with clustering or combining protocol.

VI. EXPERIMENTAL ANALYSIS

In this section, we evaluated our proposed method on different datasets using Matlab on windows-7 of 32-bit based PC with Intel i3 2.53 GHz and 3GB RAM. To understand the performance of proposed work under different conditions we used Oliver Research Laboratory (ORL) database. Classifier that has been used to find out the recognition accuracy of our proposed algorithm is K-Nearest neighborhoods classifier. The experimental results have been compared with different previous known methods as Eigen face based PCA [2], Multi fractal dimension feature based along with proposed method.

In the experimental analysis we partitioned the datasets randomly into two sets, one for testing and other for training. Each dataset implemented with different size and nature of illumination and expression variations. In each dataset the sample ratio of training and testing images has been represented as training/testing.

In Experiment the feature selection has been done on the original dataset without performing face cropping and normalization. The Experiment performed with controlling the amount of variations in each dimension judged by the program in each mode manually. Main motive behind Experiment was to find out the effect of shadows and presence of hair in feature selection.

1. **Face Recognition using ORL Database**

   To understand the working of proposed method we used original ORL dataset of 400 images with size of 92x112 pixels of 40 individuals with 10 faces of each individual. Pre-processing methods have been used for face finding and normalisation on above dataset used for our experimentation. Some example of dataset has been shown in figure below.

Figure 5: Example images from ORL dataset

Here for experiment we are starting the training from one image of each individual up to nine images of each and rest for testing. Based on experiment the results are presented in table below. Based on 1/9 (training/testing) sample ratio we found 77.16% accuracy and 98.90% accuracy when took 9/1 (training/testing) sample ratio. Here no need to perform any variance control as we have taken the facial part only

Table 1- Results based on ORL Dataset based on KNN classifiers

Sample Ratio (training/testing)	PCA	PCA-LDA	MFD (Multi Fractal Dimension)	PCA-MFD
1/9	69.39%(40)	71.05%(40)	73.28%(7)	**77.16%**
2/8	83.31%(80)	84.87%(40)	85.50%(7)	**87.38%**
3/7	88.00%(60)	89.43%(40)	90.50%(9)	**91.34%**
4/6	90.92%(78)	92.17%(40)	91.75%(9)	**93.42%**
5/5	92.50%(53)	95.00%(40)	95.00%(9)	**96.50%**
6/4	92.38%(79)	94.25%(40)	96.13%(8)	**96.72%**
7/3	94.67%(76)	96.33%(40)	95.50%(8)	**96.97%**
8/2	95.50%(63)	95.50%(40)	96.75%(10)	**98.58%**
9/1	95.50%(21)	95.50%(40)	97.50%(10)	**98.90%**

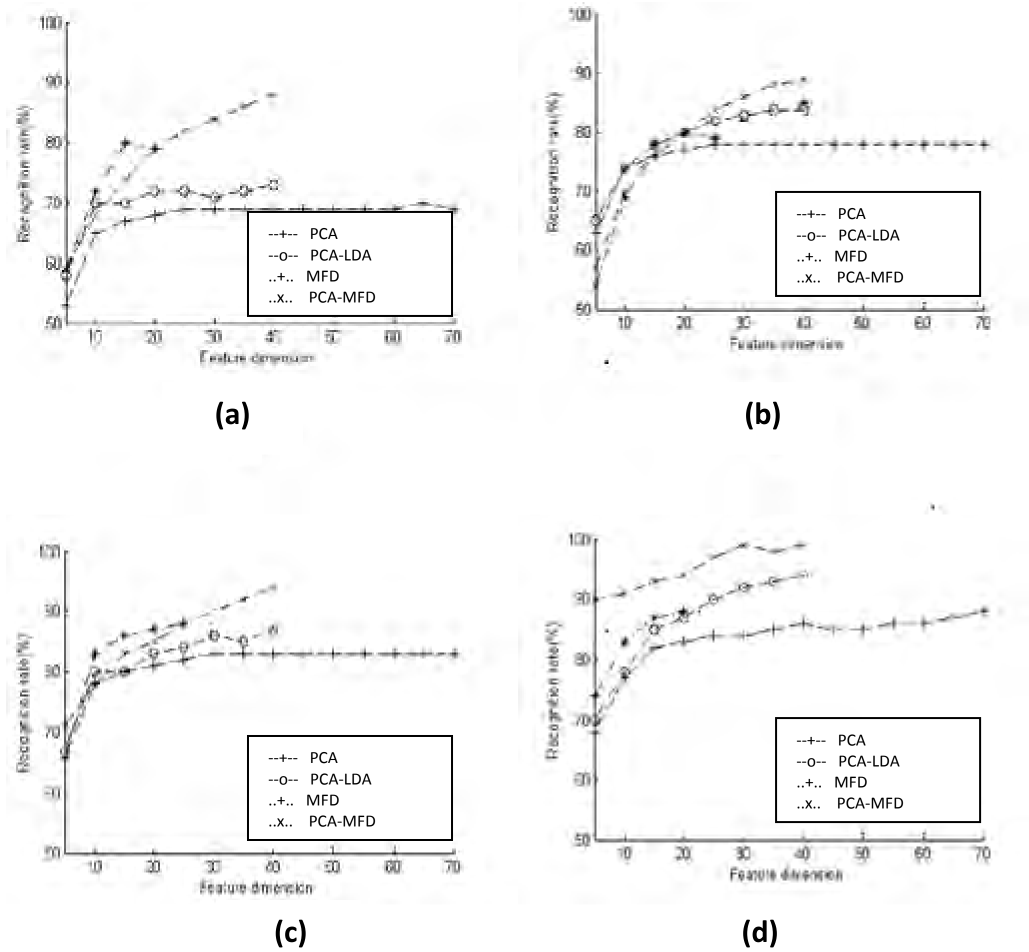

Figure 6: Recognition rate against feature Dimension of all four methods: (a) with two images taken for training (b) with three images taken for training (c) with four images taken for training (d) with five images taken for training of each training sample

Further analysis is performed to understand the ability of quality feature selection of proposed method with an increase in training data size. When 2/8 sample ratio has been used on PCA PCA-LDA, MFD and proposed method then recognition accuracy of proposed method gradually increases and found its superiority when it comes with its optimal feature size. Initially when fewer features have been used with small training size proposed method shows lower recognition accuracy. The reason behind this lies in way of feature selection of these methods. Further when 5/5 or higher sample ratio has been operated on proposed method; we found better recognition accuracy than other methods. On further increment in Sample ratio the recognition has also increase greater than previous methods. It shows that proposed method work well for larger dataset than other methods. The result analysis has been shown in above figure and table.

2. Face Recognition using YALE Database

To test our method we used YALE data set. YALE database contains 165 face images of 15 individuals human with 11 images per person class in GIF format. Each of the 11 images is different with respect to their centre-light, right-light, left-light, with and without glasses and different facial appearance (normal, sleepy, wink, surprised, happy and sad). Some example of dataset has been shown in Figure.

Figure 7: Example images from YALE dataset

Yale dataset used in order to understand the end result on recognition rate when there is illumination variation comes with expression. Several experimentations have been done with different sample ratio starting from 2/9 to 9/2. In Experiment with 8/3 sample ratio, 97.77% recognition rate has been shown by proposed method. On further increment in sample ratio we found slight decrement in recognition accuracy because of some variations in hair style of last images of each person class. The results analysis has been given in table-2.

Table 2- Results based on YALE Dataset

Sample Ratio (training/testing)	PCA	PCA-LDA	MFD	PCA-MFD
2/9	45.19(32)	48.15(42)	49.63(10)	**54.07**
3/8	49.17(30)	55.83(40)	76.30(10)	**83.70**
4/7	56.19(30)	64.76(36)	79.17(9)	**89.17**
5/6	64.44(26)	68.89(30)	83.81(9)	**91.43**
6/5	78.67(25)	81.33(28)	87.78(7)	**97.33**
7/4	83.33(25)	88.33(28)	89.33(8)	**96.66**
8/3	91.11(26)	93.33(25)	93.33(9)	**97.77**
9/2	86.67(30)	90.00(25)	90.00(9)	**93.33**

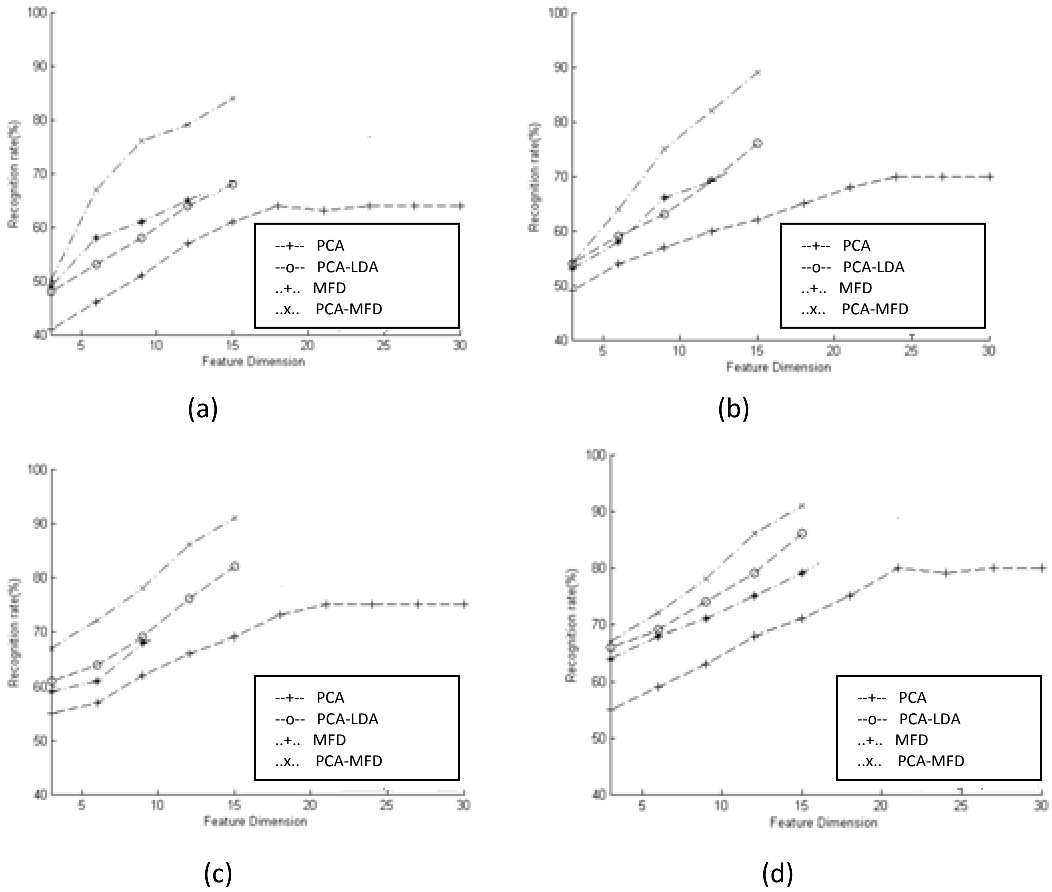

Figure 8: Recognition rate against feature Dimension of all four methods: (a) with two images taken for training (b) with three images taken for training (c) with four images taken for training (d) with five images taken for training of YALE database

VII. Conclusion

We have suggested a new algorithm based on Intensity based Multi-Fractal Dimension and PCA. Algorithm has been tested on ORL and YALE datasets with and without pre-processing techniques. We observed that proposed combination of MFD and PCA is more powerful under different illuminations and various expressions than previous methods such as PCA, LDA, PCA-LDA, and MFD. When data size has been increases the recognition accuracy also increases. In each case with increase in training size, the recognition accuracy of the suggested system shows its superiority when examine with other existing methods. It ensures that proposed method is suitable with larger datasets. Although it shows better results than existing methods, under pose and illumination variations but a slight degrade in accuracy when there is a more variation in illumination is present. Finally it can be conclude that proposed PCA-MFD method work well under illumination variation, pose variations and under shadow effect with promising accuracy and efficiency even with larger dataset size.

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