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Human Identification System Based on Face using Active Lines Feature among Face Landmark Points

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Abstract

Nowadays, Face is a crucial field for many Pattern Recognition researchers. It is considered as a good way for biometric authentication in many surveillance systems. The most important issue in Face recognition is the features extraction from the Face's images of the person's images or videos. In this paper a proposed method has been introduced to identify person images, which are captured by cameras. This method depends on the distance values between Face landmark points. Gain ratio attribute (feature) selection has been used to choose the Active Lines (ALs) that lead to the highest identification rate. The proposed method was evaluated against BioID Face database, to recognize person from one image. The experimental results reveal the effectiveness of our proposed method against other Face recognition methods to achieve a better accuracy.

Keywords: *Feature Extraction, Face Identification, Biometric Authentication and Gain Ratio Attribute Selection*

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1. Introduction

Biometric-based technologies include identification based on physiological characteristics (such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear and voice) and behavioral traits (such as gait, signature and keystroke dynamics) [1]. Face recognition is a task so common to humans, that the individual does not even notice the extensive number of times it is performed every day. Although research in automated Face recognition has been conducted since the 1960's, it has only recently caught the attention of the scientific community.

Many Face analysis and Face modeling techniques have progressed significantly in the last decade [2]. However, the reliability of Face recognition schemes still poses a great challenge to the scientific community [3]. Facial recognition holds several advantages over other biometric techniques. It is natural, non-intrusive and easy to use. The basic Face information consists of [2]: ***Landmarks set*** is a set of x and y coordinates that describes features (here facial features) like eyes, ears, noses, and mouth corners. ***Geometric information*** is the distinct information of an object's shape, usually extracted by annotating the object with landmarks. ***Photometric information*** is the distinct information of the image, i.e. the pixel intensities of the image. Moreover, ***Shape*** is all the geometrical information that remain when location, scale and rotational effects are filtered out from an object.

The face recognition technique can be broadly divided into three categories: methods that operate on intensity images, methods that deal with video sequences, and methods that require other sensory data such as 3D information or infra-red imagery [4]. Liposcak and Loncaric. [5] reported a 90% accuracy rate using subspace filtering to derive a 21 dimensional feature vector to describe the Face profiles and employing a Euclidean distance measure to match them on a database of 30 individuals, Swets and Weng [6] reported 90% accuracy, when employing the Fisherfaces procedure, on a database of 1316+298 images from 504 classes. Nefian and Hayes [7] reported 98% using embedded Hidden Markove Method (HMM) face models on the ORL database. Haddadnia *et. al*. [8] used PCA, the Pseudo Zernike Moment Invariant (PZMI) [2] and the Zernike Moment Invariant (ZMI) to extract feature vectors in parallel, which were then classified simultaneously by separate RBF neural networks. The outputs of these networks were then combined by a majority rule to determine the final identity of the individual in the input image. Jain *et al.* [9] performed the super classifier based on a voting scheme for the entire video sequence using 174 images of the eyes of 29 people (6 images per person), good recognition results (97.7% accuracy) have been reported. Gordon [10] calculated the principle curvatures of the face surface from range of data.

The system was tested using the Face images of 8 people (3 images per person), recognition rates of 97% and 100% were reported for individual features and the whole face respectively. Culter. [11] applied the eigenface technique to a database of 288 hand-aligned low-resolution (160x120) images of 24 subjects taken from 3 viewpoints. The following recognition rates were reported: 96% for frontal views, 96% for 45 degrees views, and 100% for profile views. Dapher [12] employed Incremental PCA-LDA Algorithm on BioID Face Database, and reported a 86.67% accuracy rate.

2. Architecture of the Proposed Model

The Face recognition problem can be formulated as follows: Given an input Face image and a database of Face images of known individuals, how can we verify or determine the identity of the person in the input image? The proposed model architecture for human identification system based on Face Recognition passes through two processes: the Learning process (Enrolment) and the Identification process (Testing) as shown in Fig. 1. The major functional units for each process will be introduced in the following sections.

The proposed model has been implemented using Matlab R2010b as a programming language. The first phase in the learning process is the preprocessing. The preprocessing phase determines the Face landmark points on the gray level image as calculated in BioID Face database [13].The second phase is the feature extraction. In this phase each captured Face image is represented by the Active Lines among Face Landmark Points (ALFLP) feature vector that will be explained later. The third phase is building the training database that contains the ALFLP feature vector of each sample for each person. Similarly, the

Identification process is partitioned into three phases which include preprocessing, feature extraction, and classification. The preprocessing and feature extraction phases are the same like the learning process. The classification process is based on the multiple classification technique models that were built by using training vectors.

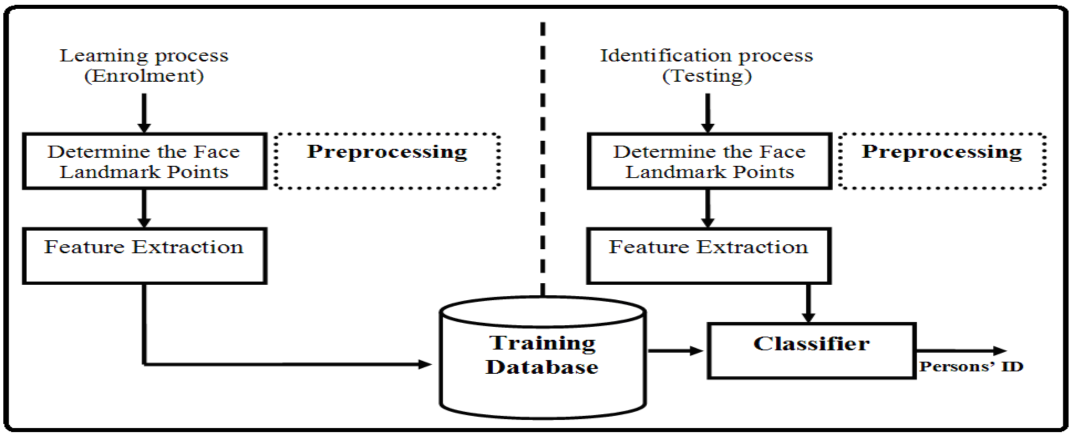

Fig. 1: The proposed model architecture

3. Pre-processing Phase

This section describes the pre-processing phase. The main target is to determine the Face landmark points on the gray level image in BioID Face datasets. The mark up scheme is as follows: 0 = right eye pupil, 1 = left eye pupil, 2 = right mouth corner, 3 = left mouth corner, 4 = outer end of right eye brow, 5 = inner end of right eye brow, 6 = inner end of left eye brow, 7 = outer end of left eye brow, 8 = right temple, 9 = outer corner of right eye, 10 = inner corner of right eye, 11 = inner corner of left eye, 12 = outer corner of left eye, 13 = left temple, 14 = tip of nose, 15 = right nostril, 16 = left nostril, 17 = centre point on outer edge of upper lip, 18 = centre point on outer edge of lower lip and 19 = tip of chin . The BioID Face database [13] is one of the largest databases that is used in human Identification using Face. The BioID database was recorded in 2001. BioID contains 1521 images of 23 persons, about 66 images per person. The database was recorded during an unspecified number of sessions using a high variation of illumination, facial expression and background. The degree of variation was not controlled resulting in "real" life image occurrences. All images of the BioID database are recorded in greyscale with a resolution of 384 × 286 pixels. Some examples from the BioID dataset are shown in Fig. 2.

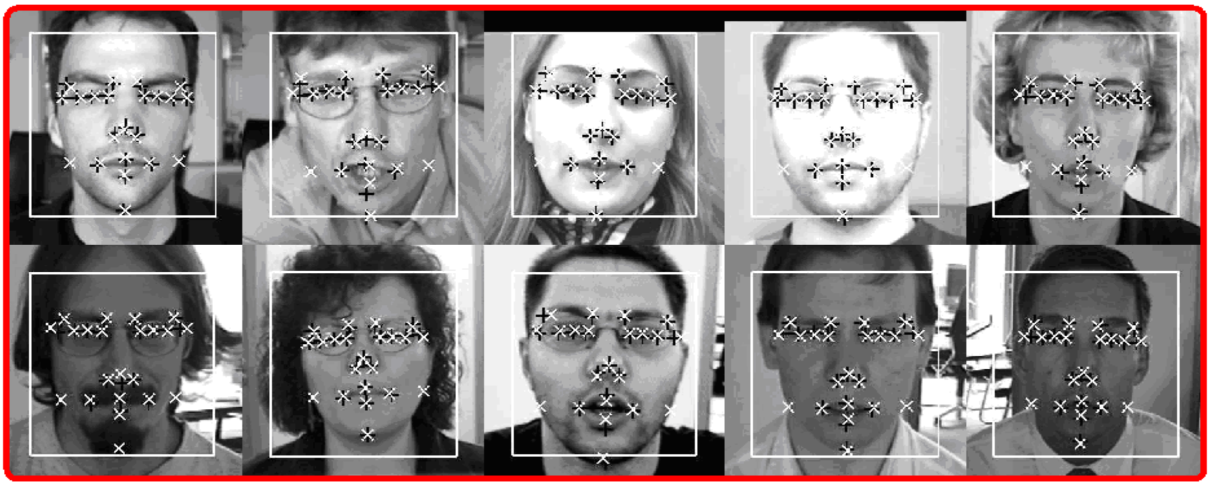

Fig. 2: Examples of BioID images with landmark points

4. Feature Extraction Phase

In this phase, two algorithms are presented. These are Feature Extraction and ALFLP algorithms.

a) ***Feature Extraction algorithm**:* The key to the success of any Face recognition system is the Face Feature Extraction. Though, this paper resorts to the use of appearance features to characterize human Face. More precisely, each pre-processed Face image contains 20 landmark points, the maximum possible lines that connect these points is 190 lines. The length of each is recorded. Thus, each Face image records a vector of the valid number of lines lengths. We denote the length of the d line by Xd, where d varies from 1 to N. The N is number of lines lengths among face landmark points and thus X = {X1, X2… XN}. These lines fulfil the description of the Face pattern, then the extracted feature vector X is divided by the maximum line value for normalization. Fig. 3 shows the Face lines between all the landmark points. Fig. 4 introduces feature extraction algorithm.

Fig. 3: Maximum number of lines among landmark points

Initialization: $d = 1$, $d = 1\ldots$ N (where d is the possible line index between two landmark points and N is the maximum number of possible lines lengths).
Step-1: Calculate X[d], where X[d] is the d-th possible distance value between two landmark points ($X[d] = \sqrt[2]{(x_i - x_j)^2 + (y_i - y_j)^2}$, where i and j are coordinates of two landmark points).
Step-2: Increment d.
Step-3: Repeat Step-1 and 2 until d = N.
Step-4: Find maximum value X_{Max} for X[d] elements.
Step-5: Divide each element in X[d] by X_{Max} to generate Normalized Face Feature Vectors (NFFV) and thus Overcoming the scaling problem.

Fig. 4: Feature extraction algorithm

b) ***Active Lines among Face Landmark Points (ALFLP) Algorithm:*** The second algorithm towards feature extraction phase is finding the ALs that can be used for person's authentication. Feature selection is the process of removing features from the data set that are irrelevant with respect to the task that is to be performed. Feature selection can be extremely useful in reducing the dimensionality of the data to be processed by the classifier, reducing execution time and improving predictive accuracy (inclusion of irrelevant features can introduce noise into the data, thus obscuring relevant features). It is worth noting that even though some machine learning algorithms perform some degree of feature selection themselves (such as classification trees), feature space reduction can be useful even for these algorithms. Reducing the dimensionality of the data reduces the size of the hypothesis space and thus results in faster execution time.

In general, feature selection techniques can be divided into two categories**:** ***filter methods*** and ***wrapper methods***. *Wrapper methods* generally result in better performance than filter methods. Different feature ranking and feature selection techniques have been proposed in machine learning literature, such as: Correlation-based Feature Selection (CFS), Principal Component Analysis (PCA), Gain Ratio Attributes Selection (GRAS), Information Gain Ratio Attributes Selection (IGRAS), Chi-Square Attributes Selection (CSAS) and Support Vector Machine Feature Elimination (SVMFE) [14]. Moreover, forward selection, backward elimination, bi-directional search, best-first search, Genetic search and other methods [14] are often used in this task.

In this paper the performance of the feature selection algorithms (GRAS, IGRAS and CSAS) are evaluated, and the classifiers chosen including a wide range of paradigms (Neural Network with multilayer perceptron, ***IBK, Kstar, NNge, J48,*** and ***FT***) are compared. In this paper, the mentioned classifiers techniques are used to evaluate the proposed ALFLP method. The used Neural Network (***NN***) classifier is a predictive model loosely based on the action of biological neurons placed in several layers.

The input layer takes the input and distributes it to the hidden layers which do all the necessary computations and outputs. The implemented ***IBK*** classifier is a K-Nearest Neighbour (***K-NN***) classifier and constructs decision boundaries by just storing the complete training data. The ***Kstar*** classifier is an instance-based classifier [15]. The ***NNge*** classifier is a Nearest-Neighbour-like algorithm, using non-nested generalized exemplars, which are hyper rectangles that can be viewed as if-then rules [16]. The ***J48*** classifier is the WEKA implementation of the ***C4.5*** algorithm [17]. The Functional Trees (***FT)*** classifier combines a standard univariate Decision Tree (***DT***), such as ***C4.5***, with linear functions of the attributes by means of linear regressions [17]. The written code was based on the WEKA data mining package and the default parameters used for each algorithm.

All experiments were carried out using a 10-fold Cross Validation (***CV***) approach to control the validity of experiments. ALFLP algorithm is presented in Fig. 5. First, select a sequence NFFV's and consider them as a Reference NFFV's (RNFFV's).Second, calculate Gain Ratio value for every attribute (distance value). Select the attribute that has the highest Gain Ratio value. Then calculate the accuracy, using ***K-NN*** (***IBK***) classifier, which achieved the best accuracy among all other classifiers. Finally, repeat the previous steps as long as the accuracy is not decreased to get all possible ALFLP. Classification accuracy is calculated by dividing the number of correct classified instances by total number of instances [14].

```
main()
  {        L= []; // Initialize ALFLP's vector.
        d =1
        Do {
             AC[d]= GainRatioValue [d] // Gain Ratio Value for d^th attribute (line)
             Increment d
           }While (d ≤ N)

             //The AC[d] is sorted in a descending order.
    Do {     Get index d of maximum value for: AC[d] and put it in the ALFLP's vector L
            Calculate the accuracy by using IBK as a classifier and put index d as a new attribute
        to L.
       } While (value of accuracy increases)
  }
```

Fig. 5 ALFLP algorithm

5. Discussion and Experimental results

To evaluate the proposed model, three experiments were performed using 23 persons from BioID database.

Experiment 1*:* In this experiment, the best feature selection technique and classifier are both selected to use them in the ALFLP algorithm. The following steps are applied using a number of feature selection techniques including CSAS, GRAS and IGRAS. The Feature

Extraction algorithm is applied on 40% from BioID database. In the classification, all attributes of the dataset have been first selected. Then cross validation of 10 folds have been chosen as test method using WEKA implementation. Table 3 shows the accuracies using Neural Network, ***IBK, Kstar, NNge, J48,*** and ***FT*** Classifiers, among different feature selection techniques including CSAS, GRAS and IGRAS algorithms. Fig. 6 shows the comparison of accuracies for the three attribute selection techniques and using six classifiers. The average accuracy for GRAS (78.699%) as good as IGRAS (78.2617%), better than CSAS (77.68%), and better than using all attributes (77.9709%) without selection. Furthermore, the Reduction Ratios (***RR***) for all attribute selection techniques are equal (15.8%).

Table 3: The resultant accuracies using six classifiers with three attribute selection techniques

Attribute Selection / Classifier	**CSAS** ***(RR = 15.8%)***	**GRAS** ***(RR = 15.8%)***	**IGRAS** ***(RR = 15.8%)***	**All Attribute** ***(RR = 15.8%)***
NN	86.9565%	87.8261%	87.8261%	87.8261%
IBK	87.8261%	87.8261%	87.8261%	87.8261%
Kstar	73.913%	73.913%	73.913%	73.913%
NNge	84.3478%	84.3478%	84.3478%	84.3478%
J48	51.3043%	56.5217%	53.913%	52.1735%
FT	81.7391%	81.7391%	81.7391%	81.7391%
Average Accuracy	**77.68%**	**78.699%**	**78.2617%**	**77.9709%**

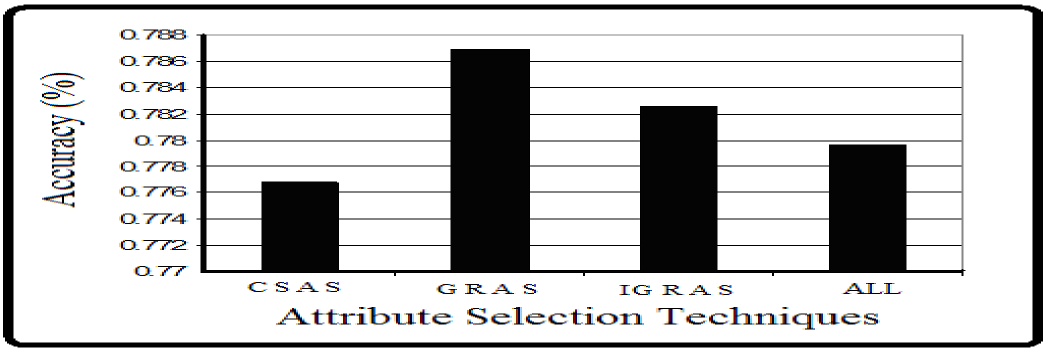

Fig. 6: Average accuracies for using different classifiers with CSAS, GRAS and IGRAS

Experiment 2*:* In this experiment, the Active ALFLP algorithm is applied to determine the best attributes with best accuracy. From experiment 1, the accuracy of GRAS technique is better than CSAS, IGRAS techniques, and better than using all attributes. Furthermore the accuracy of ***NN*** and ***IBK*** classifiers were better than ***Kstar, NNge,*** and ***FT*** classifiers and superior than ***J48*** classifier. Therefore, the GRAS technique and ***IBK*** classifier were selected to perform the ALFLP algorithm. Fig. 7 shows the accuracy results for different number of ALFLPs based on cross validation of 10 folds as a test method using the ***IBK*** classifier on

10% from BioID Face Database. It could be noticed that the minimum number of ALFLP's is 26 lines that achieve the best accuracy (86.316 %). Table 4 represents the two terminals of the ALFLP vector.

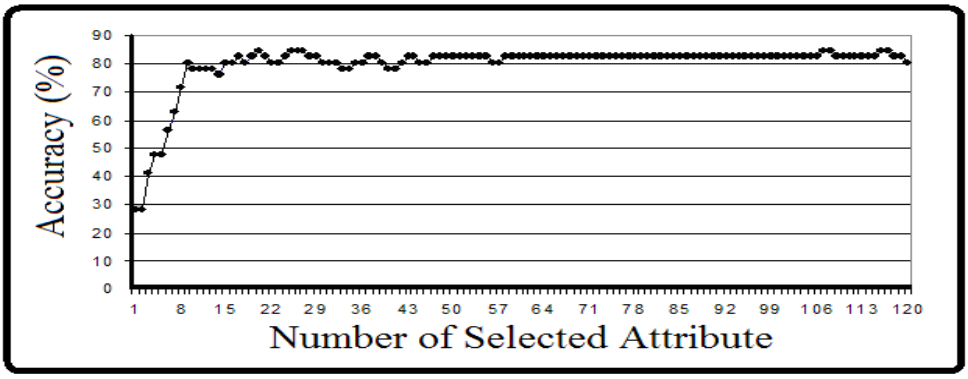

Fig. 7: Accuracy results for different number of ALFLP

Table 4: ALFLP vector.

Line No.	ALFLP's	First Landmark Point	Second Landmark Point
1	X[107]	6 (inner end of left eye brow)	15 (right nostril)
2	X[5]	0 (right eye pupil)	5 (inner end of right eye brow)
3	X[65]	3 (left mouth corner)	14 (tip of nose)
4	X[103]	6 (inner end of left eye brow)	10 (inner corner of right eye)
5	X[25]	1 (left eye pupil)	6 (inner end of left eye brow)
6	X[6]	0 (right eye pupil)	6 (inner end of left eye brow)
7	X[45]	2 (right mouth corner)	10 (inner corner of right eye)
8	X[159]	11 (inner corner of left eye)	16 (left nostril)
9	X[1]	0 (right eye pupil)	1 (left eye pupil)
10	X[150]	10 (inner corner of right eye)	15 (right nostril)
11	X[86]	5 (inner end of right eye brow)	6 (inner end of left eye brow)
12	X[63]	3 (left mouth corner)	12 (outer corner of left eye)
13	X[7]	0 (right eye pupil)	7 (outer end of left eye brow)
14	X[95]	5 (inner end of right eye brow)	15 (right nostril)
15	X[66]	3 (left mouth corner)	15 (right nostril)
16	X[106]	6 (inner end of left eye brow)	13 (left temple)
17	X[15]	0 (right eye pupil)	15 (right nostril)
18	X[145]	9 (outer corner of right eye)	19 (tip of chin)
19	X[158]	11 (inner corner of left eye)	15 (right nostril)
20	X[87]	5 (inner end of right eye brow)	7 (outer end of left eye brow)
21	X[73]	4 (outer end of right eye brow)	7 (outer end of left eye brow)
22	X[182]	15 (right nostril)	17 (centre point on outer edge of upper lip)
23	X[57]	3 (left mouth corner)	6 (inner end of left eye brow)
24	X[105]	6 (inner end of left eye brow)	12 (outer corner of left eye)
25	X[62]	3 (left mouth corner)	11 (inner corner of left eye)
26	X[70]	3 (left mouth corner)	19 (tip of chin)

Experiment 3**:* This experiment was implemented to study the effect of the training dataset's size on the accuracy. Different portion of BioID Face database (10%, 20%… and 90%) are used as training dataset size. Six Classifier techniques (NN, IBK, Kstar, NNge, J48*** and ***FT***) are used to choose the best classifier achieving the best accuracy with the best training portion of BioID Face database. Since the size of training dataset is very important in module building time. Table 5 shows the accuracies for the used six classifiers and ALFLP selection method. All classifiers are implemented at portions of BioID Face database as training dataset. Fig. 8 shows the accuracies of the six classifiers used: ***NN, IBK, Kstar, NNge, J48*** and ***FT***. The experimental results indicate that the obtained accuracy using ***NN*** is the best and the accuracy obtained by ***IBK*** and ***FT*** are better than that produced by ***Kstar, NNge,*** and ***J48***.

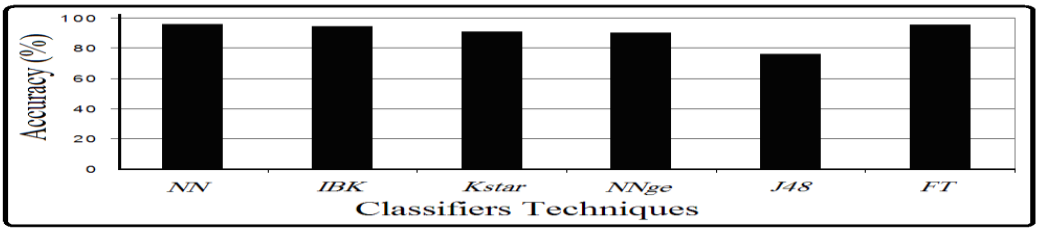

Fig. 8: Accuracy results for different classifiers.

Table5: Accuracies of six classifiers for different portions of BioID Face database as training dataset.

% Trained / Classifier	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	Average Accuracy
NN	*91.7%*	*93.9%*	*94.3%*	*93.4%*	*95.9%*	*96.1%*	*96.7%*	*96.4%*	*96.1%*	*99.7%*	**95.41%**
IBK	*89.6%*	*91.7%*	*92.4%*	*93.1%*	*94.9%*	*95.1%*	*94.9%*	*94.7%*	*96.1%*	*100%*	**94.25%**
Kstar	*85.8%*	*88.7%*	*90.7%*	*91.2%*	*91.2%*	*91.8%*	*91.9%*	*92.1%*	*91.4%*	*93.7%*	**90.84%**
NNge	*79.1%*	*85.52 %*	*88.5%*	*89%*	*91.2%*	*91.4%*	*92.1%*	*90.5%*	*91.4%*	*100%*	**89.9%**
J48	*56.1%*	*68%*	*73.5%*	*75.1%*	*73%*	*80.3%*	*78.9%*	*79.3%*	*80.3%*	*97.2%*	**76.17%**
FT	*90.8%*	*92.9%*	*94.1%*	*93.9%*	*95.9%*	*95.4%*	*96.3%*	*95.7%*	*96.7%*	*100%*	**95.19%**

6. Comparative study

To evaluate the performance of the proposed model we should compare it with some global models. This experiment was performed to compare our proposed Face recognition method with the Incremental PCA-LDA (Principle Component Analysis-Linear Discriminant Analysis) algorithm in [12]. This algorithm computes the principal components of a sequence of vectors incrementally without estimating the covariance matrix and at the same time computing the linear discriminant directions along which the classes are well separated. Fig. 9 shows the comparison of Face recognition performance of our proposed method with the Incremental PCA-LDA algorithm in [12], using ***IBK*** classifier, 40% and 60% training dataset, and 10-foldes Cross Validation techniques for testing. The experimental results show that the accuracy of our proposed algorithm using 40% training dataset is 93.0997%, superior than IPCA-LDA (75.01%), using 60% training dataset is 95.0658%, superior than IPCA-LDA (72.45%), and using 10-folds Cross Validation is 96.4497%, better than IPCA-LDA (86.67%).

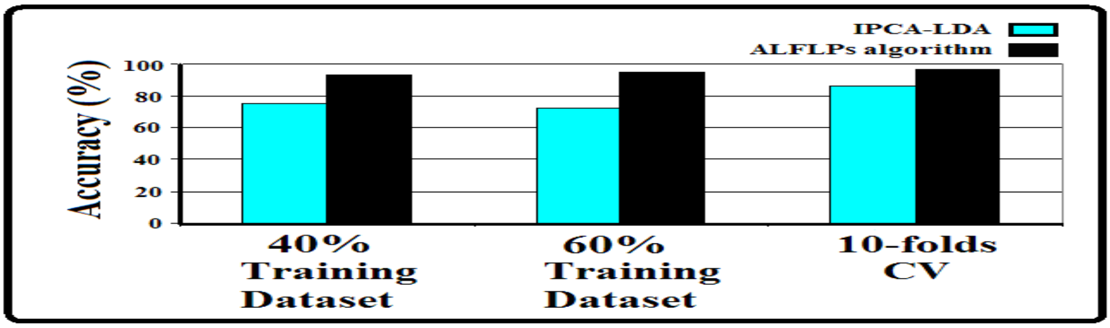

Fig. 9: Accuracies results comparing our proposed method with the IPCA-LDA method in [12]

7. Conclusions

This paper has addressed the problem of Face recognition based on appearance features in human Faces, with considering the issues of distance metrics and scales. Our major contribution lies on offering a promising method to extract Face feature (ALFLP). These features are invariant under scale, transform, and illumination. Experimental results on BioID Face Database [13] indicate that the proposed algorithm is better than that algorithm proposed in [12] in case of using 40% Training dataset, 60% Training dataset, and 10-folds Cross Validation.

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