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Multi-Modal Facial Recognition Based on Improved Principle Component Analysis with Eigen Vector Feature Selection

[1]*A. Manchula and* [2]*S. Arumugam*

[1]Faculty of Computer Science and Engineering, Nandha College of Technology, Perundurai, Erode
[2]Principal Nandha Engineering College, Perundurai, Erode, India

Abstract: Physiological biometric behavior such as face is taken in our research work to verify the individual's identity. The process involved in biometric system is feature detection and recognition process. However, face recognition is hard case on the biometric object recognition with higher performance result. Most of the existing face recognition system takes longer time to produce the performance result, due to the more dimensionality distractions. For better recognition accuracy, new face feature extractions are needed to be explored. To develop an effective face recognition system, Multi-modality Face Feature Recognition System based on the Principle Component Analysis Eigenvector Selection (PCAES) Method is proposed in this paper. Initially, Invariant Face Region Feature Detection operation extracts the face from the total training image of the users. Secondly, the new face features are selected using the Eigen vector selection through branch and bound process. For the effective face classification process in PCAES Method, new logistic regression learning classification process predicting the outcome of a face categorical dependent variable with lesser dimensions. Finally, Principle Component Procedure with R3 rule procedure increases the recognition level accuracy. PCAES finds the new training multi-modality data representation in the subspace of smaller size which maximizes the dimensionality reduction level. The reduction of dimensionality reduces the distraction level. Case study and preliminary experimental results conducted in viable PCAES approach on proving the 2D and 3D facial recognition. Experiment is conducted on factors such as, feature extraction indexing rate, false acceptance rate, false rejection rate and recognition accuracy level.

Key words: Face Recognition · Principle Component Analysis · Eigen Vector Selection · Logistic Regression Learning Classification · Branch and bound

INTRODUCTION

The facial features from the users are is easily collectible, general and non intrusive biometric quality. Face recognition process defines the matching of the test image individuals with the training template images. Face recognition is the most difficult crisis due to varying nature in faces and variations caused by several factors such as expressions, gender, pose, illumination and make up [1]. Biometrics consists of methods for identification of human face features based on the nature of physical traits which works in the following ways. They are feature detection and recognition mode as in fig 1.

The templates can be of a smart card, user name or user id which is used for comparison. The feature detection process involves one to one comparison.

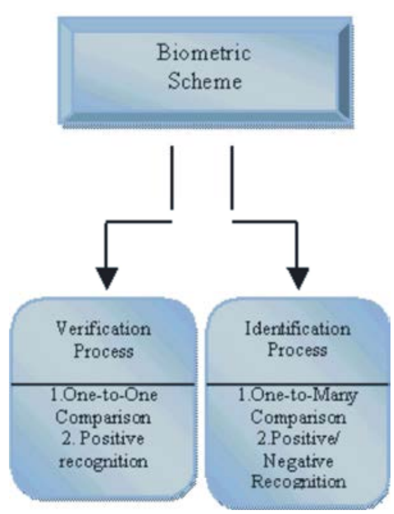

Fig 1: Conceptual Biometric scheme

Corresponding Author: A. Manchula, Faculty of Computer Science and Engineering, Nandha College of Technology, Perundurai, Erode, India. E-mail: manchuselva@gmail.com.

The common use of feature detection mode is used for "positive recognition". In recognition mode, the process involves assessment against a biometric database by matching an individual's biometric with the template of every identity in the database. Comparison results are based on the value of threshold. The process achieves higher rate if the comparison of biometric test data to a stored training data which lies within the threshold value. The common use of recognition mode is either "positive recognition" or for "negative recognition"[2].

The recognition is performed to check the individual's actual face matching rate. The human face is not a unique with the rigid object. The several factors that cause the appearance of the varying face. The sources of dissimilarity in the facial appearance are sort out into two forms such as intrinsic feature and extrinsic features. Intrinsic feature are merely due to the physical nature of the face and are autonomous of the observer. These factors further divided into intrapersonal and interpersonal behaviors. Extrinsic feature root the appearance of the face to regulate via the interface of light with the face and the viewer. The feature includes illumination, pose, size and imaging restrictions.

Existing Linearly Approximated Sparse Representation-based Classification (LASRC) algorithm as described in [1] uses linear regression step to carry out sample collection of the features. A pair-matching verification task is carried out on the open-universe web-scale data identification. However, the complicated method is not developed on rejecting distractors and tighter the integration with minimization algorithms. The dimensionality is also not reduced, so that the performance speed up rate is reduced. To reduce the dimensionality rate, [3] presented two dimensional principle component analyses (2DPCA). 2DPCA also extracts the features in the linear order. The extracted features are classified with minimum distance algorithm but more evaluation is needed for recognition operation.

In this work, focus is made on developing an effective multi-modality face recognition system using PCA with Eigenvector Selection. Proposed Principle Component Analysis Eigenvector Selection (PCAES) method performs the face detection, feature extraction, face classification and recognition process. Face detection process for the effective biometric recognition of objects using Invariant Face Region Feature Detection operation. Then the features are extracted using Eigenvector selection with branch and bound process [4]. The extracted features are classified using new logistic regression learning classification process. Finally, the face is recognized using Principle Component Procedure with R3 rule procedure.

The structure of this paper is as follows. In Section 1, describes the basic problems in biometric recognition of the multi-modal face features. In Section 2, present an overall view of the Principle Component Analysis Eigenvector Selection (PCAES) method. Section 3 and 4 draw experiment results with parametric factors and present the result graph for research on biometric recognition of objects. Finally, Section 6 concludes the work with better result outcome [5].

Literature Review: Traditional face recognition techniques mostly depend on low-resolution face images, which fallout in the lost of important information that are contained in the microscopic traits. In paper [2], initiate a multilayer structure for handling the images of high resolution face recognition. The recognition system develops features in multiple scales. Each face image is factorized into four layers such as universal appearance, facial organs, skins and asymmetrical feature details. However, the algorithms experience from a variety of confines like applicability, efficiency, strength to resolution and the discriminating capability of the used feature representation. In [6] a novel feature matching algorithm is developed for automatic pair-wise checking of range test and training images which leads to higher dimensionality rate.

Multi-Kernel Appearance Model (MuKAM) in [7] explores the efficient multi-scale landmark detectors to reduce the dimensionality rate. Multi-kernel classifiers are combined with multi-scale landmark detectors, where the two-stage framework is reliable among points for approximating the parameters of a shape model. Face shape model based on the probability of the facial landmark detector reduces the cost factor with Gauss–Newton algorithm. MuKAM needs to achieve the higher robustness factor while interacting with face recognition on real-world conditions.

A various number of new face recognition techniques is presented in existing work [8]. Some of them include recognition from three-dimensional (3D) scans, recognition from high resolution still images, recognition from multiple still images, multi-modal face recognition, multi-algorithm and preprocessing algorithms to exact for illumination and pose variations. The paper [9] discusses about Face Recognition Vendor Test (FRVT). Present 2D face recognition systems attain high-quality performance in constrained environments. However face with difficulties while managing large amounts of facial variations such as head pose, lighting situations and facial expressions [10].

As the human face is a 3D object whose 2D projection is sensitive to the above changes, utilizing 3D facial information improves the face recognition performance. Oxytocin facilitates the dealing out of out-group faces and decreases the Own-Race Bias (ORB) in [11]. Oxytocin uniformly well recognizes the black and white faces but does not produce the feasibility result rate. The Geometrix FaceVision3D faces recognition technology as presented in [5], illustrate about the shape and texture fusion.

In paper [7], a multimodal hybrid face recognition algorithm is demonstrates and performance is carried out on the FRGC v1.0 data. A hybrid model feature-based and holistic matching for the 3D faces and a holistic matching approach on the 2D faces are examined. Three schemes such as non-linear clustering, Eigen vector mapping and relationship learning are used in [12] to build up a human based and machine based recognition system. Relationship learning among Very Low Resolution (VLR) images to the High Resolution (HR) image space is not capable on concentrating with non faces real time recognitions.

In paper [3] presents technique for extracting characteristic invariant features from images which is used to perform matching among diverse views of an object. This approach has been called as Scale Invariant Feature Transform (SIFT). For face image matching and recognition, SIFT features are initially extracted from a set of reference images and stored in a database. A new test image is matched by evaluate every feature from the training image to decide the candidate matching features based on Euclidean distance of their feature vectors. The paper [3] discusses in detail about the fast nearest-neighbor algorithms that perform this multiplication quickly against large databases [13].

The performance of face recognition systems that employ 2D images depending on factors such as lighting and subject's pose. 2Dimage in [4] develops a face recognition system that makes use of 3-dimensional shape information to make the system more vigorous to arbitrary pose and lighting. For each step, a 3D face model is constructed by combining numerous 2.5D face scans which are captured from different views. A fully automatic 3D face recognition algorithm is presented in paper [8]. Several novelties such as automatic 3D face detection, repeated pose correction and normalization of the 3D face, a Spherical Face Representation, use as a rejection classifier and robustness to facial expressions are included [13].

3D face detected using the phase based representation in, where the structural context model jointly encode the outputs of face detector and body detector. The structural model encodes the prior data, such as the landmarks of face and body which fully explored in traditional face detection models. Paper [9] talk about multi-view correspondence algorithm to connect the free form objects. The multi-view correspondence algorithm automatically create connection in the midst of the unordered 2.5D views of a free-form object by performing a one-to-many correspondence search using a 4D hash table.

The result in a spanning tree of comparative transformation among the unordered views used to roughly record them in a general coordinate basis. The registration process is additionally refined using multi-view fine registration followed by the integration and renovation of the views into a seamless 3D model.

Multimodal approaches moreover combine 3D geometry with 2D texture or with 2D IR data. Most of these works utilize small datasets and do not focus on handling facial expressions. The paper [10] focuses on large datasets by way of using wavelet analysis to take out a dense biometric signature, thus allowing us to carry out quick comparisons on either a global or a per area basis. Data normalization is applied separately on the 2D and 3D data. The normalized images are used for the PCA and edge-based approaches. The ICP-based approach does not necessitate a broad normalization result. Details of the steps for normalization are found in [11].

Multi-Modality Face Feature Recognition System: The proposed work presented a multimodal (i.e., different face expressions) face recognition system based on principle component analysis. Principal Component Analysis is a statistical procedure concerned with elucidating the covariance face structure with set of variables for recognition. In particular PCAES allows us to identify the principal directions in which the face feature varies. Initially the face is detected from the user using Invariant Face Region Feature Detection through Fuzzy Hough transform. The face region feature detected carried out by analysis of edge points found in the image. In terms of computational complexity PCAES method outperforms the result when compared with existing system.

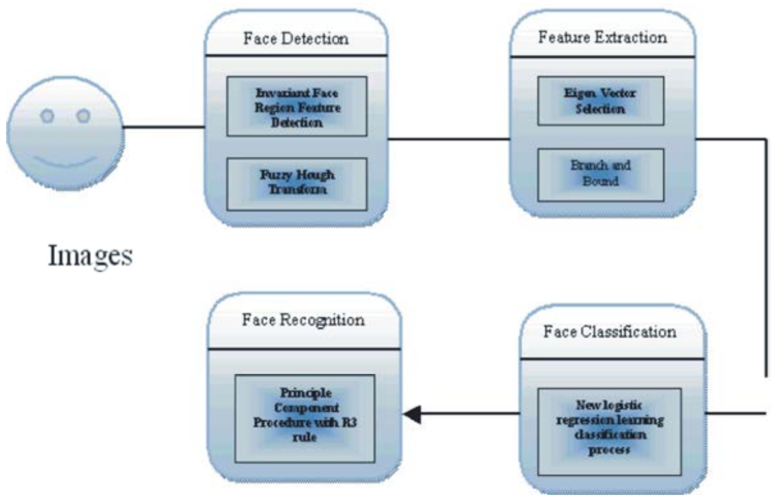

Fig 2: Architecture Diagram of Multi-modality Face Feature Recognition System

Overall Architecture of the Multi-modality Face Feature Recognition System: The Multi-modality Face Feature Recognition System consists of four phases. The first phase consists of face detection using the Fuzzy Hough transform. Second phase follows the feature extraction process. The feature extracted is used on classification of the face. Finally the classified multimodal face features are recognized using Principle Component Procedure with R3 rule procedure. The architectural diagram of proposed work is as presented in fig 2 [14].

Initial phase of the Multi-modality Face Feature Recognition System is the Invariant Face Region Feature Detection. The edge points of the face are detected to find invariant features of a face. The invariant features remove unwanted pixels from the images based on the statistical value. Second phase consists of the feature extraction using the Eigen vector selection. The extended features extracted are shape of the eyes, nose and jaw are selected by discarding the non relevant feature using branch and bound in PCAES Method [15].

The third phase is the face classification in PCAES Method by way of minimizing the dimensionality and computational complexity. New logistic regression learning classification process classifies the features for the easy recognition. Finally, the last phase involves the face recognition approach that is performed using Principle Component Procedure with R3 rule. Template matching process compares input images with stored training images [16].

Fuzzy Hough Transform: The PCAES Method uses the, Invariant Face Region Feature Detection to extract the face multimodal features from the user's gallery. The invariant face region is extracted through Fuzzy Hough Transform in proposed work. Hough transform easily localize the face shape from the images on the source of the object edges. Shape detection is carried out by analysis of edge points found in the image. The two dimensional image space in the PCAES Method contains the face image matrix of FI_{m*n}. The gradient value is used on detecting the face with edge points 'P' is determined as,

$$x_i = x_p \, sign\,(\Delta x_p) = \frac{a_i}{\sqrt{1+\frac{b_i^2}{a_i^2}(\frac{\Delta y_p}{\Delta x_p})}} \tag{1}$$

x_i denotes the 'x' coordinate axis face detected with the edge points 'P'. The axes a_i and b_i are considered as the accumulators. ΔX_P are the overall coordinate edge points are detecting the face. Similarly, 'y' coordinates face edge points are detected as,

$$y_i = y_p \, sign\,(\Delta x_p) = \frac{b_i}{\sqrt{1+\frac{a_i^2}{b_i^2}(\frac{\Delta x_p}{\Delta y_p})}} \tag{2}$$

PCAES Method, off course detects the face shape by applying the fuzzy Hough transform. The fuzzy rule is directly proportional to the gradient value in the specified edge points. Fuzzy Hough Transform uses the spherical face representation to quickly exclude a large proportion of the candidate classes. The class with higher probability rate on spherical based preference level quickly eliminates a large number of candidate faces at an early stage for efficient recognition of larger galleries. The effectiveness on excluding the unrelated candidate class is denoted as,

$$\textit{Spherical based Preference Level}\ (\mu) = \frac{P_{a\epsilon S}(\mu\ (a,b))}{G} \quad (3)$$

Where, the spherical based preference level ‘μ’ is used on detecting the face by removing the unrelated class. The edge points ‘P’ of the ‘x’ and ‘y’ axes is clearly illustrated with set of class labels $_{a\ ^{a}\ S.}$ G is the size of gallery where the users information is placed in the PCAES method [17].

Eigen Vector Selection: Eigen vector selection works to extract the features of the face in PCAES method, where Eigen Vector ‘EV’ is

$$EV = \{f_1, f_2, \ldots f_n\} \quad (4)$$

Note that, different multimodal feature vectors have the different dimensionalities. The eigenvectors of two dimensional points is employed using the branch and bound process to extract the features. Branch and Bound procedure in PCAES method consists of the systematic splitting of the face features from the detected candidate face images. The Branch and Bound design paradigm follows the discrete and continuous optimization to extract the face features. The multimodal face features such as eyes, nose and jaw are selected using the Eigen vector selection. The Eigen vector value is represented as ‘1’, when the features are easily extracted from the face image set.

New Logistic Regression Learning Classification Process: The new logistic regression learning system works in PCAES method to classify the face features. PCAES method is a probabilistic view of the classification system which gives the high predictive accuracy. A class assigned with the new logistic threshold value for the effective classification of the feature space. Logistic regression learning helps to predict the output using the training images.

$$P = \frac{1}{1+e^{-\sum_{f=1}^{N}\beta_i(xy_{i,j})}} \quad (5)$$

The probabilistic classification view of the face features uses the natural log function for the effective classification of the biometric face features. The multimodal feature space of 1, 2 and 3….N is used for classification. β may be the regression coefficients of the ‘x’ and ‘y axis ‘j’ variable at the observation ‘I’.

Principle Component Procedure with R3 Rule: Facial recognition system identifies a person based on the feature extraction of facial components with the help of known faces. In PCAES work, perform face recognition system based on known faces with the help of principle component procedure with R3 rule matching. Principle component analysis in the proposed work is a process which concerned with identifying the principle directions of face recognition. Each regression coefficient is a principle component, used for the recognition process.

The mathematical description about the Principle component analysis in proposed work deals with the Eigen vector selection. The features extracted with the eigenvector form helps to easily recognize the face with R3 procedure. R3 procedure uses the full regression coefficient based classification result is used to perform the recognition operation. Recognition with R3 procedure in PCAES work helps to decide the test images and training image matching interest. New logistic regression learning classification result is used in R3 procedure set for multimodal face recognition.

Multi-modality Face Feature Recognition System-Algorithm: Begin

Step 1: Scan the input image for face detection.

//Face Detection:

Step 2: Perform Face Detection using Invariant Face Region Feature Detection.

Step 2.1: Uses the Fuzzy Hough transform.

//Feature Extraction:

Step 3: Perform Feature Extraction based on the extraction process using Eigen vector selection.

Step 3.1: Branch and Bound process carried out

Step 3.2: Features like shape of the eyes, nose and jaw are selected by minimizing the dimensionality and complexity

//Face Classification:

Step 4: Face classification is performed using new logistic regression learning classification process

Step 4.1: Classification of face features are performed

//Face Recognition:

Step 5: Recognized face feature through Principle Component Procedure with R3 rule

Step 5.1: Perform matching which compare input test images with stored training features.

End

The above algorithmic procedure compares the multimodal face feature recognition with existing work. Face feature reduce the comparison to false rate by 0.03% which proves to be a better approach in PCAES, when compared with existing system. The invariant face is detected on in the initial step. Then features such as eyes, forehead, jaw and nose regions are extracted through the branch and bound process. The features extracted are used on the new logistic regression learning system for classification. The results of classification process are used with the R3 PCA procedure to recognize the features.

Experimental Evaluation: The experimental evaluation of Multi-modality Face Feature Recognition System based on the Principle Component Analysis Eigenvector Selection (PCAES) Method is performed in MATLAB code. PCAES method is compared against the existing system. A Matlab implementation on a 2.3-GHz Pentium IV machine took 6.2 ms to construct a classifier of a probe, match it with the 455 images in the gallery and reject a subset of the gallery with 2,363 ms for the same purpose. Method helps to perform the comparison process with the available human face dataset.

Efficient Principle Component Analysis Eigenvector Selection (PCAES) Method are conducted and presented herewith. The performance of PCAES is compared to the spin images when used as rejection classifiers. The probes were performed with both neutral and non-neutral expression. For probes with a neutral expression, the face images performed better result whereas for probes with non-neutral face expression is lesser in result rate. The results performed based on the face recognition prove to be more efficient than the existing image classifier.

Principle Component Analysis Eigenvector Selection work performs the face detection and extraction as shown in Fig 3. The spherical structure representation is used on detecting the face in PCAES method. Experiment is conducted on the factors such as feature extraction indexing rate, false acceptance rate, false rejection rate and recognition accuracy level. The amount of the face features extracted effectively from the users face images is defined as the feature extraction indexing rate. The False Acceptance Rate (FAR) is defined as the number of images correctly accepted from the whole set of the test images.

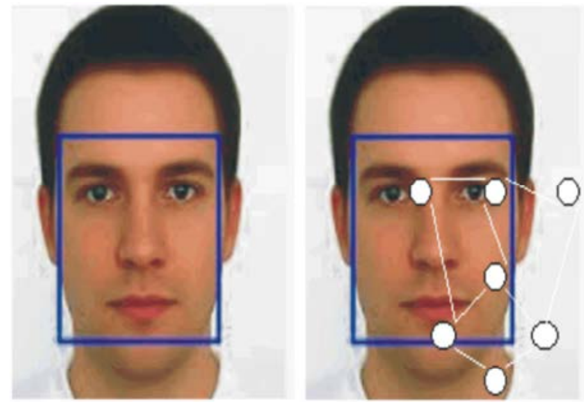

Fig 3: (a) Face Detected (b) Face Feature Extracted

$$FAR = \frac{No.of\ face\ image\ accepted}{No.of\ images\ tested} * 100$$

The false acceptance rate is lesser in proposed work, where the detection threshold is about 0.05 percentages. The threshold R_{th} is of 0.05 is attained then the lesser false acceptance carried out. The false rejection rate is the total amount of images is recognized accurately from the whole set of the test images. False rejection rate is measured in terms of percentage (%).

$$FAR = \frac{No.of\ face\ image\ rejected}{No.of\ face\ images\ tested} * 100$$

The threshold R_{th} is of 0.05 is attained then the higher false rejection is carried out in PCAES. The amount of the accurate face biometric recognized from the test samples is defined as the recognition accuracy level. The Expected Error Rate (EER) on recognition is defined as the frequency of error occurred on recognizing the face images.

$$Expected\ Error\ Rate\ (EER) = \frac{No.of\ errors}{Total\ no.of\ face\ images\ on\ test}$$

The parameters that is more associated with analyzing the overall proposed system performance. Error rate shows the performance in terms of error percentage (%).

RESULT AND DISCUSSION

The result of PCAES is compared with the Linearly Approximated Sparse Representation-based Classification (LASRC) algorithm and Multimodality Face Recognition System (MFRS). The below table and graph briefly described about the experimental work.

Feature extraction indexing rate measures the indexing efficiency based on the feature count. The features such as eyes, nose and jaw are selected using the Eigen vector selection. Eigen vector selection improves the indexing rate by 18 – 28 % in PCAES method when compared with the LASRC Algorithm [1]. Vector uses the Eigen value for indexing the extracted features with the high efficiency rate. The extraction is about 5 – 8 % improved in PCAES method when compared with the MFRS.

Fig 5 describes the false acceptance rate based on the instances. As the number of instances increases, the FAR for is decreased in PCAES method when compared with LASRC Algorithm. The eigenvectors of two dimensional points is employed using the branch and bound process to reduce the false acceptance rate. Then if the detected threshold is attained, the false acceptance is reduced to 22 – 41 % when compared with the LASRC Algorithm. Similarly, Branch and Bound procedure in PCAES method is employed to improve the speed of the false acceptance rate. The procedure of PCAES reduces the false acceptance by 13 – 37 % when compared with MFRS.

Fig 6 demonstrates the no of instances as the 'x' axis and the rejection rate is plotted along the 'y' axis value. As increase in number of instances, gradually increases the rejection rate. The rejection rate is improved by introducing the Fuzzy Hough transform in PCAES method. Shape detected through the spherical representation of the edge points, thereby improves the rejection rate by 7 – 21 % when compared with LASRC Algorithm. The detected face through the fuzzy Hough transform rule improves the rejection rate by 16 – 49 % when compared with the MFRS.

Fig 7 illustrates the recognition accuracy level based on the feature selected. The Principle component analysis with R3 procedure uses the classification result to improve the recognition rate by 9 – 12 % when compared with the LASRC Algorithm [1]. The features extracted with the eigenvector form helps to easily recognize the face with R3 procedure in PCAES when compared with MFRS [2]. New logistic regression learning classification result is used in R3 procedure. The result percentage is 2 – 6 % improved in PCAES when compared with MFRS.

Table 1: Feature Extraction Indexing Rate Tabulation

	Feature Extraction Indexing Rate (%)		
Feature Count	LASRC Algorithm	MFRS	PCAES method
2	0.69	0.81	0.89
4	0.71	0.83	0.90
6	0.75	0.84	0.92
8	0.78	0.85	0.93
10	0.79	0.89	0.94
12	0.80	0.90	0.96
14	0.81	0.91	0.97

Table 2 False Acceptance Rate Tabulation

	False Acceptance rate (Acceptance %)		
No. of instances	LASRC Algorithm	MFRS	PCAES method
10	0.075	0.063	0.051
20	0.082	0.068	0.0591
30	0.0639	0.0754	0.0512
40	0.0845	0.0845	0.053
50	0.0923	0.0622	0.054
60	0.0756	0.0745	0.050
70	0.0745	0.0825	0.058

Table 3:False Rejection Rate Tabulation

	False Rejection rate (Rejection %)		
No. of instances	LASRC Algorithm	MFRS	PCAES method
10	0.0375	0.0422	0.0513
20	0.0477	0.0512	0.0571
30	0.0439	0.0474	0.0512
40	0.0345	0.0465	0.0515
50	0.0393	0.0422	0.0504
60	0.0356	0.0445	0.050
70	0.0405	0.0475	0.0512

Table 4:Tabulation of Recognition Accuracy Level

	Recognition Accuracy Level (%)		
Features Selected	LASRC Algorithm	MFRS	PCAES method
5	82	87	90
10	84	90	93
15	86	92	94
20	78	82	86
25	82	87	92
30	79	84	87
35	84	88	93
40	86	90	96

Table 5:Tabulation of Expected Error Rate

	Expected Error Rate (Error %)		
No. of face images	LASRC Algorithm	MFRS	PCAES method
7	2.56	2.88	1.81
14	3.20	3.83	2.38
21	8.16	9.20	6.12
28	6.69	7.62	5.13
35	4.45	5.67	3.46
42	9.17	10.25	6.38
49	10.35	11.27	7.85

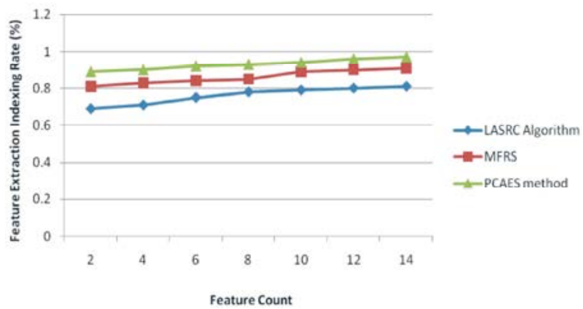

Fig 4: Feature Extraction Indexing Rate Measure

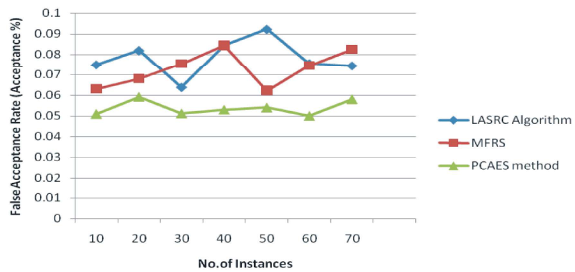

Fig 5: False Acceptance Rate Measure

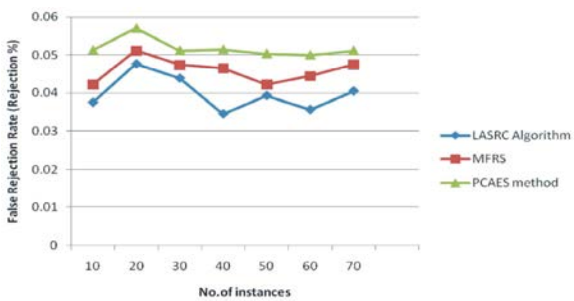

Fig 6: False Rejection Rate Measure

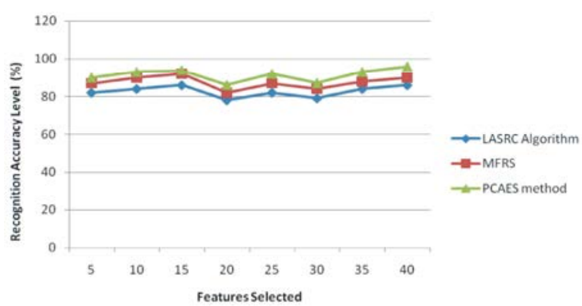

Fig 7: Measure of Recognition Accuracy Level

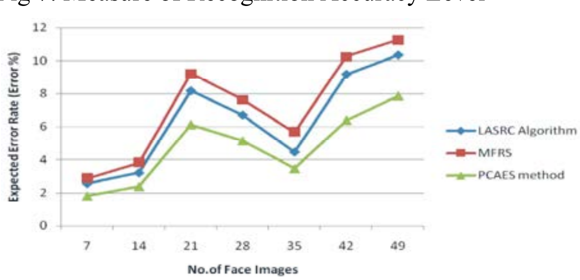

Fig 8: Measure of Expected Error Rate

Expected Error rate measured based on the face image taken for the experimental work. The logic regression with the coefficients helps to easily recognize the error rate. PCAES with the probabilistic view reduces the error rate to 22 – 30 % when compared with LASRC Algorithm [1]. A class assigned with the new logistic threshold value for the effective classification of the feature space, thereby reduce the error rate by 30 – 38 % when compared with the MFRS [2]. The multimodal feature space is also recognized with lesser error rate percentage.

CONCLUSION

PCAES method is presented to demonstrate the effectiveness of the multimodal face feature recognition system. Invariant Face Region Feature Detection operation on the initial stage uses the Fuzzy Hough Transform. The transformed face then performs the extended multi-modal feature extraction using Eigen vector selection. The Eigen vector uses the Eigen value points with branch and bound procedure for continuous splitting of features from the face. Feature invariant methods through Eigen vector selection discards angle and position using branch and bound technique.

Then the new logistic regression learning classification process predicts the features trough the probabilistic view. Finally, the classified face feature space is recognized using the principle component analysis with R3 procedure. Several experiments have been conducted with image size variant to 256 * 256 pixels of image in order to evaluate the performance of the PCAES algorithm. FAR is reduced to 13 – 37 % when compared with MFRS and FRR is improved by 7 – 21 % in PCAES when compared with the LASRC Algorithm. The decrease in false acceptance rate and improvement in the false rejection rate, in turn reduces the complexity rate.

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