Face Recognition Using Improved FFT Based Radon by PSO and PCA Techniques

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Abstract

Face Recognition is one of the problems which can be handled very well using Hybrid techniques or mixed transform rather than single technique. This paper deals with using of Radon Transform followed by PCA and LDA techniques for Face Recognition. The data used are 2D Face Images from ORL Database. The Radon Transform used is based on FFT slice theorem. The directions along which the Radon transform is performed are selected using PSO in order to achieve a good recognition rate. The best directions selected are less computation expensive as compared to the full set of directions and achieve good recognition rate. The PCA is used to reduce the dimension of the data produced by Radon Transform and the LDA is used to find a set of basis vectors which maximizes the ratio between-class scatter and within–class scatter. In order to verify our method many dataset partitioning scenarios into training set and testing set were conducted. And the maximum recognition rate achieved was 97.5%.

Keywords: Face Recognition (FR), Radon Transform (RT), Fast Fourier Transform (FFT), Principal Component Analysis (PCA), Linear Discrimenant Analysis(LDA) and Particle Swarm Optimization (PSO).

1. INTRODUCTION

Face recognition is one of the most important biometrics which seems to be a good compromise between actuality and social reception and balances security and privacy well. It has a variety of potential applications in information security law enforcement and access controls. Face recognition systems fall into two categories: verification and identification. Face verification is 1:1 match that compares a face images against a template face image. On the other hand face identification is 1: N problem that compares a probe face image against all image templates in a face database. Face recognition is a very difficult problem due to a substantial variations in light direction (illumination) , different face poses , diversified facial expressions , Aging (changing the face over time) and Occlusions (like glasses, hair, cosmetics). So the building of an automated system that accomplishes such objectives is very challenging. In last decades many systems with recognition rate greater than 90% has been done however a perfect system with 100% recognition rate remains a challenge. Face recognition algorithms are divided by [1, 2] into three categories as follows:

1. Holistic methods: These methods identify a face using the whole face images as input and extract the overall features.
2. Feature based methods: these methods used the local facial features for recognition (like eyes, mouths, fiducial points. etc.).
3. Hybrid methods: these methods used both feature based and holistic features to recognize a face. These methods have the potential to offer better performance than individuals.

2. A REVIEW OF THE RELATED 2-D FACE RECOGNITION TECHNIQUES

Thomas Heseltine [3] investigated three appearance based approaches for face recognition which are the direct correlation method, the eignface method and fisherface method. the recognition error rate reported is 18% , 20.4% , 17.8% respectively .

M. Chandra Mohan[4] they divide the face into four parts and evaluates the texture features in each part separately the texture features are derived from parameters with different orientations, this makes the face recognition easier and pose, illumination and rotation invariant.
P.Abouzar [5] using WT (Wavelet) and DCT (Discrete Cosine Transform) followed by PCA the proposed algorithm takes advantages of data reduction property of the three transforms. The Support Vector Machine (SVM) was used to classify the images into different classes and the error rate obtained is between 5%-7%.

Zhan Shi[6] they extract a number of features from facial images through taking Trace Transform over different angular directions by using different trace functions then the features are projected into a lower dimensional subspace. The recognition rate achieved is 95% in ORL database.

Laika Karsili [7] used a Radon Transform over the set of angles{0,60,120,180,240,300,360}, then the produced data was reduced using PCA this achieves 70% recognition rate for rank 1 and 95% for rank 4.

Jamal A hmad [8] Investigated the effect of the step size for both the angle and the vector of the radon transform on the performance of a face recognition system based on PCA it is founded that step size of one for both produces recognition rate of 89%.

ZHANG et al, [9] proposed a feature extraction method based on finite Radon transform (FRAT) then used soft threshold (ST) to select main FRAT coefficients. Finally 2DMMC was used to extract features for classification from main FRAT coefficients. They achieved 89.02% recognition rate on ORL database.

Ergun Gumus et al [10] they used Eigenfaces (PCA) and Support Vector Machine (VSM) on ORL database they achieved recognition rate of 91,2% for PCA-AVM (RBF) Radial bases.

Zhang Lin et al [11] used Radon Transform with multiwavelet and PCA on Infrared imaged faces and they achieved 95% classification accuracy with 70 element feature vector.

Yuehui Chen et al [12] proposed using DCT and Hybrid Flexible Neural Tree which was evolved using PSO their experiment on ORL achieved 98.13% recognition rate .

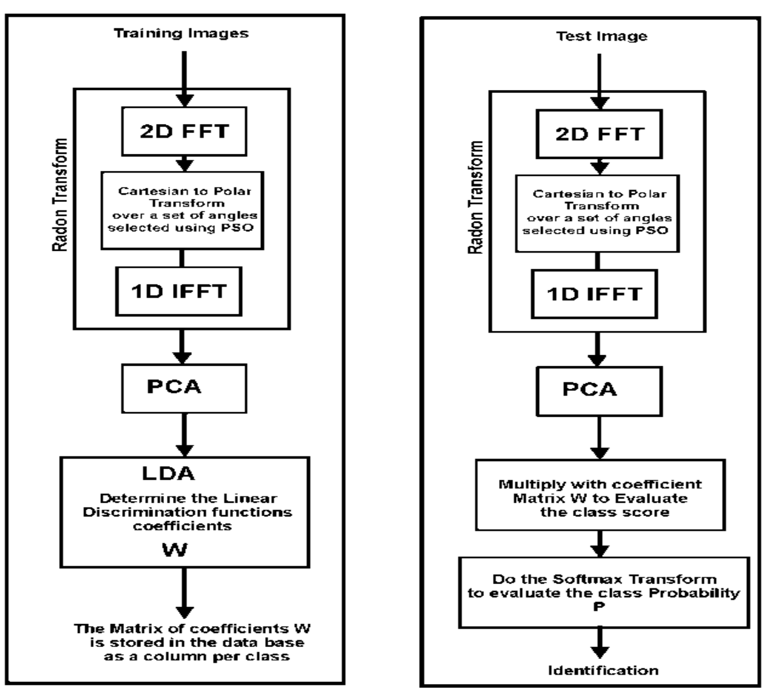
Jian Zhang , Xianyun Fei[13] they used the PSO in order to select the optimum discrimination eigenvectors of PCA and obtain the optimal recognition accuracy simultaneously they validate their method with ORL database with recognition rate of 96%.
Dattatray V. Jadhao and Raghunath S. Holambe[14] they used Radon transform and Fourier transform for face recognition on ORL database and achieved recognition rate of 97.33% the images were classified on the nearest neighbor with 60 features .

Rabab M.Ramadan [15] used PSO to select the efficient features from DCT and DWT and apply their method on ORL with recognition rate 94.7% and 96.8% respectively .

In this paper we used the Radon Transform which is improved by PSO to select the best directions. Then a data reduction is performed using the PCA. A classification basis vectors are derived using LDA which lead to a rank one recognition rate equal to 97.5% and the feature vector size is 35 items per class (person).

3. THE METHOD AND MATERIALS

The method used in this paper for face recognition is depicted in figure (1). It consists the enrollment phase and the testing phase. In the enrollment phase the training set of images are transformed into Radon space using the Radon Transform. The set of directions (angles) along which the transform is performed were calculated using the Particle Swarm Optimization (PSO). Different sets of directions are shown in tables (1, 2, 3). The different sets are for different classifier parameters which yield a good estimated recognition rate. The data generated by Radon Transform are reduced using Principal Components Analysis (PCA). From those reduced data set (i.e. the most effective components) a set of basis vectors which maximizes the ratio between-class scatter and within–class scatter using Linear Discrimenant Analysis (LDA). One basis vector for each class (i.e. Person) is derived and stored in the data base. So for ORL Image database there are 40 basis vectors are stored regardless of the number of images used for each person in the training set. The length of the basis vector depends on the number of components selected by the PCA stage. In the testing phase the input image is transformed into the Radon space using that set of directions which were used in the enrollment phase. The PCA reduction is carried out as same as in the enrollment phase. The resultant vector is projected into the basis vectors stored in the data base that is by inner product method. The highest product value which must be higher than a predetermine threshold measures the similarity between the input image and the specified class. The method which is stated in this paper was evaluated using the ORL data base which contains photographs of faces taken at the Olivetti Research Laboratory in Cambridge between April 1992 and April 1994.There are 10 different images of 40 distinct subjects so there are 400 images in the data base. The images are grayscale with a resolution of 92 x 112. For some of the subjects, the images were taken at different times. There are variations in facial expression and pose variation about 20 degrees and there is some variation in scale of up to about 10%. There are some faces with glasses. Some images are shown in figure (2). In the following sections the discussion of each main part of the method of process is presented.



a:Enrollment Phase b: Identification Phase

FIGURE 1: Block diagram for the recognition system.

3.1 Radon Transform

There were many applications of Radon transform like Pose Estimation [17],Texture Analysis [18], X-ray crystallography and Nuclear Magnetic Resonance(NMR)[19], Image Matching for translation, rotation and uniform scaling Using Radon Transform[21]. Several definitions of the radon transform existed. A very popular form expresses lines is:-

$$t = x * \cos(\theta) + y * \sin(\theta) \qquad (1)$$

Where θ is the angle and t is the smallest distance to the origin of the coordinate system. The Radon transform for a set of parameters (t, θ) is the line integral through the image f(x, y), where the line is positioned corresponding to the value of (θ and t) in Equation (2).

$$g(t,\theta) = \iint_{-\infty}^{+\infty} f(x,y)\delta\big(t - x\cos(\theta) - y\sin(\theta)\big)dx\,dy \qquad (2)$$

In the above equation $g(t,\theta)$ is the Radon Transform of the f(x,y) function at a specified value of t and θ . The Radon transform can be calculated using FFT by applying the central-slice theorem [13] which is stated that the 1-D Fourier transform of the integral projection at angle θ is equal to the slice of the 2-D Fourier transform at the same angle. With the central-slice theorem the Radon transform can be computed equivalently with 2-D FFT, a Cartesian-to-polar mapping, and a 1-D FFT. The range of the θ is [0...179] and the range of the variable (t) depends on the dimension of the underling image. In our case the t is in the range [1...112] and θ range is [0...179] that is for full range directions. So each image is represented in Radon space as a vector of dimensions equal to (180 x112) = 20160. In our work a subset of θ is selected from the full range using Particle Swarm Optimization (PSO). The subset of θ values is selected according to the goodness of the recognition rate achieved as the objective function. Using different values of parameters used by the classifier a different subset are selected using PSO. Figure (3) shows a full range of θ Radon transform and figure (4) shows a subset of θ Radon transform.

3.2 Particle Swarm Optimization (PSO)

PSO, first introduced by Kenny and Eberhart in 1995 [22], is one of the evolutionary computation technology based on swarm intelligence. In a PSO system each solution called a "particle", particles fly around in the search space of the problem to look for the optimal solution. Each particle adjusts its position according to the flying experience of its own and the experience of neighboring particles. Each particle updates its velocity and position using the following equation [23]:-

$$V_i(k+1)=V_i(k)+c1 * rand1(\,pbest(k) - X_i(k)) + c2* rand2(\,gbest(k) - X_i(k)) \qquad (3)$$

$$X_i(k+1)=X_i(k) + V_i(k+1) \qquad (4)$$

Where ,

V_i is called the velocity for particle i;
X_i is represent the position of particle i ;
Pbest is the best position of ith particle
gbest is the global best position ;
rand is random variable in [0,1];
c1 and c2 are the learning factors;
w is called the inertia weight

To search for optimal solution, each particle changes its velocity according to equation 3. The value of V_i is clamped to the range [Vmin, Vmax] to avoid excessive roaming of particle outside the search space. Then each particle moves to a new potential solution using equation 4. This process is repeated until a stopping criterion is reached. The above equations (4,5) are the basic equations and not guarantee the global solution. Using those equations PSO may be trapped in local minima to avoid the local minima there are many variations and improvements to the basic equations have been suggested [24-37]. In this work we used the PSO in order to select the best set of directions (the values of θ) to be used in Radon transform. These set is selected from the full set of θ from 0 to 179 in step of 1 degree. There are 24 particles in the swarm are used with randomly selected values of θ. These particles moved and evolved towards the best positions that yield a good Recognition rate. The objective function was constructed in order to optimize both the recognition rate and the number of directions (θ) selected as well. Three sets are depicted by tables(1 ,2,3) for three values of N which is the length of the features vector used by the classifier associated with objective function used. In our experiments, the set with N=60 was used. One thing that be mentioned about PSO is its convergence to a steady state of accepted recognition rate very quickly and in stable manner.

3.3 Feature Reduction Using (PCA)

The PCA is a statistical method for reducing data dimensions [37,38]. In PCA the training data is used in obtaining the Eigen basis vectors. Then the training set R and testing set T are projected into those vectors. The PCA can be summarized by the following steps:-

a. Calculate the mean M of the training set and subtract it from the training set:

$$M = \frac{1}{n}\sum_{i=1}^{n} R_i \qquad (5)$$

For all training set perform $R_i = R_i - M$

b. Calculate the Eigenvectors and Eigenvalues of the training set covariance matrix S_t

$$S_t = R \;\; . R^T \qquad (6)$$

and pick the Eigen vectors corresponding to the N largest Eigen values of S_t. These construct the N principal components matrix (V).

c. The Basis vectors matrix (U) is constructed as:

$$U \;\; = V \;\; . R^T \qquad (7)$$

d. The reduced feature vector is calculated for training and testing data as:

$$W_R = R \;\; . U \qquad (8)$$

$$W_T = T \;\; . U \qquad (9)$$

The mean M must be subtracted from the testing data T also. Many experiments were conducted using different numbers of Eigenvectors (N) between (10-60) and the performance are reported in figure(5,7).

3.4 Linear Discrimenant Analysis (LDA)

The LDA finds a set of basis vectors which maximizes the ratio between-class scatter and within –class scatter [37]. Given N samples of C classes, let Ni be the number of samples in the ith class Ci , let Mt be the mean of the whole data set, mi be the mean of the ith class Ci, the between-class scatter matrix is defined by:

$$S_B = \sum_{i=1}^{c} N_i \; (mi - Mt) \;\; (mi - Mt)^T \qquad (10)$$

And the within-class scatter matrix is defined by

$$S_w=\sum_{i=1}^{c}\sum_{mk\in ci} (mk-mi)\ (mk-mi)^T \qquad (11)$$

Then the basis vectors is

$$W=\arg\max\left(\frac{|W^T S_B W|}{|W^T S_w W|}\right) \qquad (12)$$

Solving Equation(9) produces a matrix W whose columns are the eigenvectors corresponding to the largest eigenvalues of $S_W^{-1} S_B$. These columns are the linear discriminant functions associated with classes as a one function for each class. These functions are stored in the database in order to perform the classification as following:

Each input vector (T) to be classified is multiplied with W matrix as ($V = T^{-1}W$) the resulting vector is the linear scores of the testing data T. The class probabilities are calculated using the softmax transform as:

$$P = \frac{\exp(V(i))}{\sum_{i\in C}\exp(V(i))} \qquad (13)$$

Where C is the set of classes. Each class represents a person in the data base. The value of P show how much the testing data T is near to a specified class, the higher value is the nearest class so the classification is done. A threshold value P can be designated with in order to reject the unknown or to do misclassification.

4. THE EXPERIMENTS

The developed face recognition method was applied to the ORL database. Five experiments were conducted. Each with different partitioning scenario to the data set and the performance was evaluated against the number of eigenvectors used see figure (5). The set of eigenvectors is {10,20,25,30,35,40,45,50,55,60}. The set of directions (angles) used for radon transform is shown in table (2). The five scenarios are:

a. Scenario #1.

In this scenario the ten images for each person are divided as 5 images for training and 5 images for testing. The images were randomly selected. The maximum recognition rate was 93% that is when 25 eigenvectors are selected. See figure (5). The Boxplot is shown in figure (6). It is appear that the median is 90.5%, and the 75th percentile is around 92.5%.

b. Scenario #2.

In this scenario the ten images for each person are divided as 9 images for training and one image for testing. The images were randomly selected. The maximum recognition rate was 97.5% that is when 35 eigenvectors are selected. See figure (5). See Boxplot at figure (6). It appears that the median is 95%, and 75th percentile around 97%.

c. Scenario #3.

In this scenario the ten images for each person are divided as 8 images for training and 2 images for testing. The images were randomly selected. The maximum recognition rate was 97.5% that is when 35 eigenvectors are selected. See figure (5). See Boxplot at figure (6). It appears that the median is 95%, and 75th percentile around 97.2%.

d. Scenario #4.

In this scenario the ten images for each person are divided as 7 images for training and 3 images for testing. The images were randomly selected. The maximum recognition rate was 97.5% that is when 50 eigenvectors are selected. See figure (5). See Boxplot at figure (6). It appears that the median is 96.7%, and 75th percentile around 96.7%.

e. Scenario #5.

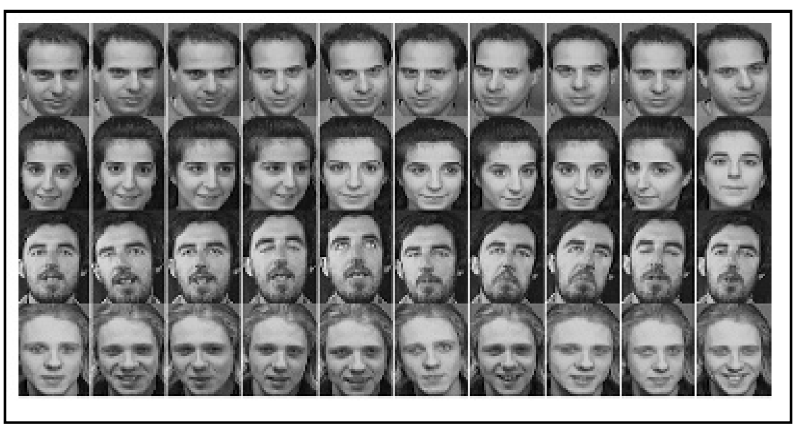
In this scenario the ten images for each person are divided as 6 images for training and 4 images for testing. The images were randomly selected. The maximum recognition rate was 95.63% that is when 60 eigenvectors are selected. See figure (5). See Boxplot at figure (5). It appears that the median is 94.4%, and 75th percentile around 94.9%.

5. DISCUSSION

In this work the using of Radon transform improves the performance of PCA+LDA techniques in face recognition. That is if compared with mentioned literature [3, 5, 7, 8, 10, and 13]. The using of PSO for selecting the best directions (angles) used by Radon transform give better performance as compared to [7,9]. This means that the subset selected using PSO is better than the one selected in [7]. From the different scenarios conducted it appears that the performance is improved with the increased number of images per person in the training set this is clear by scenario #2 ,#3,#4 . From Boxplot in figure (7), which shows the performance against the number of eigenvectors used over all scenarios in our experiment, it is clear that the number of eigenvectors between (30-40) gain the good performance. It is also clear that the (35) eigenvectors is the best.

6. CONCLUSIONS

A Face Recognition method has been described in this work. The core of this work is to apply the PCA+LDA in Radon space rather than directly to the images. The images are transformed using Radon Transform with a specified angles (directions) set determined using PSO in order to achieve good recognition rate with less computation expensive. The Radon transform used in this method was FFT based. The full range Radon transform is computational expensive if it is performed for angles from 0 degree to 180 degree and for a large number of offsets. To reduce the computations required a subset of angles and offset must be selected. So the PSO was used to select that subset and maintaining a good recognition rate. This method was verified on ROL data base using five different scenarios for training set selection. The best recognition rate was 97.5% when only 35 eigenvectors are used. The number of eigenvectors determines the length of the signature vector that be used for each person in the data base. The recognition rate and the size of signature that represent each person as well as the computation of Radon transform that a achieved in this method is better than the related works stated in the literature review in section 2.



2 : Samples from ORL Database

77 angles calculated using PSO N=60							
2	4	11	19	21	23	26	28
29	35	36	39	40	41	42	43
44	46	47	51	52	57	58	59
61	62	65	68	71	73	75	79
80	81	83	84	85	89	90	92
93	95	96	98	99	100	106	108
111	112	119	120	122	126	131	134
124	125	126	130	132	134	135	137
135	140	141	144	145	146	149	155
156	161	162	174	178			

TABLE 1 : angles calculated using PSO N=60

84 angles calculated using PSO N=10							
1	6	8	10	11	12	14	15
17	20	25	28	30	32	33	35
47	49	52	53	54	56	58	59
60	61	62	63	64	68	69	70
71	72	73	75	79	80	84	85
92	95	96	98	103	104	105	108
109	110	114	115	116	119	121	122
124	125	126	130	132	134	135	137
138	142	143	146	151	152	153	154
156	159	161	166	168	169	170	171
172	173	175	179				

TABLE 2: angles calculated using PSO N=10

88 angles calculated using PSO N=32							
1	3	4	6	10	11	16	23
24	25	26	27	28	31	32	33
34	35	36	38	42	43	46	47
48	51	52	53	55	57	58	60
61	62	64	73	79	82	86	87
89	91	92	97	98	99	100	101
103	106	107	108	109	112	118	119
120	121	122	123	124	125	126	128
129	134	136	140	141	142	145	147
149	150	151	152	153	156	158	162
163	164	166	168	171	175	176	177

TABLE 3: angles calculated using PSO N=32

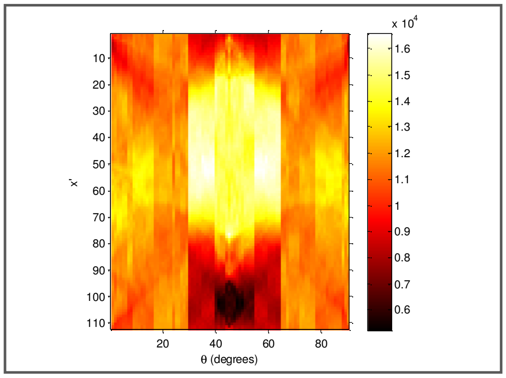


FIGURE 4 :FFT Based Radon Transform using 90 angles transform for an image calculated using PSO

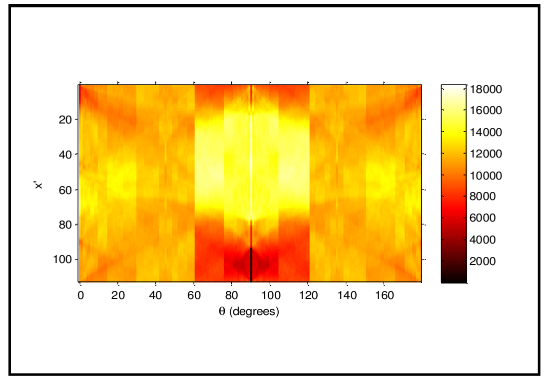


FIGURE 3: FFT Based Radon for an image

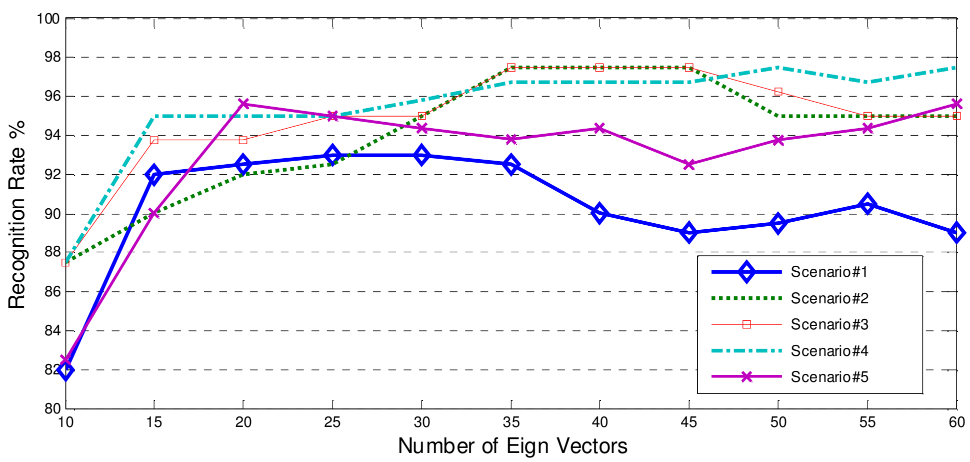


FIGURE 5: Performance against #of eigenvectors for different scenarios.

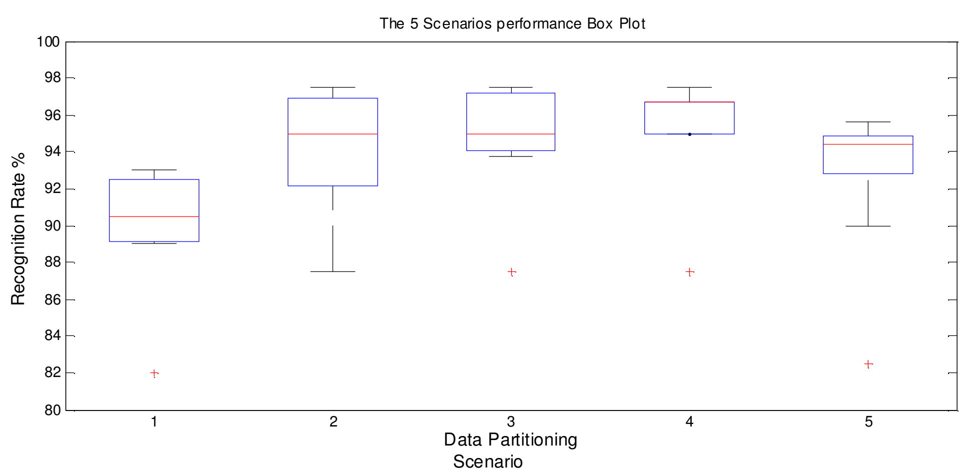


FIGURE 6: Box Plot show the performance for each scenario.

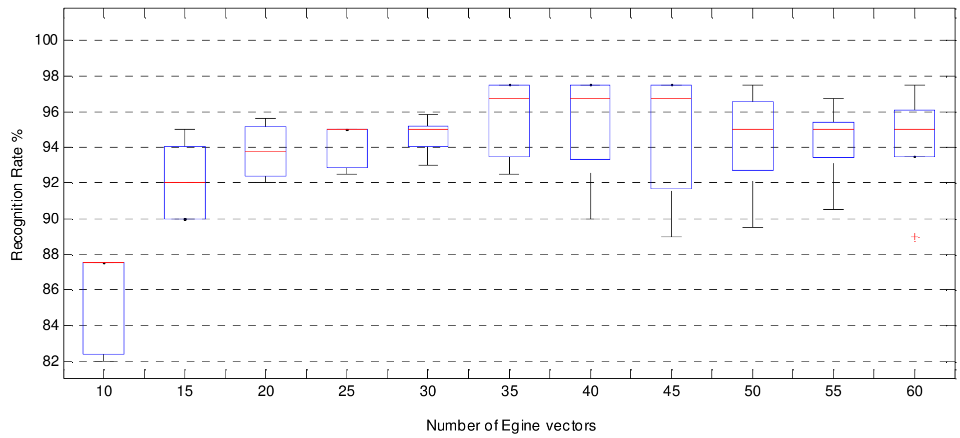


FIGURE 7: Box plot shows the performance against #of eigenvector cross the 5 scenarios.

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