International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 31 • 2017

Face Classification using Robust Linear Collaborative Discriminant Regression Classification

R.G. Dabhade[a] and L.M. Waghmare[b]

[a]Research Scholar, National Institute of Electronics & Information Technology, Aurangabad, India

E-mail: rgdabhade75@gmail.com

[b]Director, Shri Guru Gobind Singhji (SGGS) Institute of Engineering & Technology, Nanded, India

E-mail: lmwaghmare@yahoo.com

Abstract: Face Recognition (FR) has attracted effective interest, because of its significance towards the real applications. Here, the Linear Collaborative Discriminant Regression Classification (LCDRC) shows a better classification result on facial image data. However, the LCDRC could not able to categorize the samples that scattered around the intersections and also it gives a poor outcome in severe lighting variations. This paper delivered a Robust LCDRC (RLCDRC) scheme for superior FR, which is improved from LCDRC. By implementing a suitable penalty function, the RLCDRC significantly maximize the Reconstruction Error (RE) between the classes and also it minimize the RE within the class. For comparison, the proposed scheme was verified on three standard database sets. Though, the proposed methodology not only out-performs LCDRC and also it proves with the superior outcome of FR.

Keywords: *Face Recognition (FR), Linear Collaborative Discriminant Regression Classification (LCDRC), Reconstruction Error (RE).*

1. INTRODUCTION

In the past few years, FR has become a growing attention research topic in human-computer interaction and computer vision, due to its extensive range applications in the areas of identity authentication, information security, video surveillance, etc. [1], [2]. In that, Automatic Face Recognition (AFR) plays a vital role in computer vision applications [3]. Generally, improving of AFR method is practically challenging, because the human facial images are varied with their facial expressions, illuminations, and lighting conditions [4]. In order to develop practical and robust AFR system, some of the concerns need to be resolved, especially on classification and feature extraction [5]. While classifying, the individual facial images are transformed into a vector, which is very high dimensional in nature. It is significant to convert a peak dimensional image space into low dimensional image space [6]. Normally, a lot of dimensionality reduction systems are there in FR, to reduce "curse of dimensionality". Traditionally, following methods are Principal component Analysis (PCA), Linear Discriminative Analysis (LDA) and Independent Component Analysis (ICA), and so on [7].

The performance of these FR methods are highly affected by the number of samples per person in the training set. Especially, when the number of samples are low, the learned sub-space projection might be deficient. PCA and LDA are ideal in terms of reducing reconstruction error, but it can be utilized only in small size samples [8]. Currently, a few classifiers are employed, to enhance the performance of AFR system such as Linear Regression Classification (LRC), Collaborative Representation Classification (CRC) and Sparse Representation Classification (SRC). The major idea of LRC is the test image vectors are transformed into training image vectors by a linear combination, but a major issue in the LRC is dimensional illumination change [9]. In SRC and CRC, the true classes are determined by utilizing the representation of error in each class. Here, the major problem is occlusion, occurred due to ideal face partition [10]. To reduce the following drawback there is a need for an upgrade LRC method. This research focus on improving the performance of LCDRC algorithm [11], a robust LCDRC is introduced. Robust LCDRC (RLCDRC) concentrates on reducing the RE by optimizing the projection matrix.

2. LITERATURE REVIEW

Hongjun et al. [12] have illustrated a technique for robust FR, which depends on dynamic rank representation model. Here, the major factors that disturb the human facial images are occlusion, illumination and various pose. Initially, this approach extracts the dynamic sub-space and discriminative portions of each specific face image. By analyzing the properties of discriminative components, the recognition protocol helps to categorize the facial images. This experiment carried on publicly obtainable database sets like AR, Extended Yale B, and ORL, to verify its accuracy, robustness and speed.

Chris HQ Ding et al. [13] have demonstrated an extended linear regression scheme for under sampled FR procedure. The author extends the LRC through the intra-class variant dictionary and SVD to under sampled FR. Here, the three different kinds of schemes are designed to rectify the low-rank concern of data matrix such as, quasi-inverse, ridge regularization and Singular Value Decomposition (SVD). The combination of intraclass and SVD is named as Extend LRC (ELRC), which provides a significant generalization ability and robust classification in under sample situation.

Changbin Shao et al. [14] have explained a classification scheme for FR, which is named as parity symmetrical based collaborative representation classification. At first, the parity symmetrical images are synthesized by employing even and odd decomposition theorem. Secondly, each query images are mentioned as a linear grouping of training samples from the extended training set, it exploits the significant representation of each reconstructed image with the appropriate contribution of each class. Finally, it generates a significant parity symmetrical demonstration of the query images and the experimental outcome is tested on the reputed facial databases.

Ze et al. [15] have illustrated a Color Channel Fusion (CCF) methodology for FR. This approach helps to identify numerous features from discriminating channels and reliable by applying the joint dimension algorithm. Experiment using two various dimension reduction techniques achieved a consistent performance than Color Channel Concatenation (CCC) technique, which deals with the various color channels equally.

Yuwu et al. [16] have presented a Linear Regression (LR) scheme, by implementing the least square algorithm, to solve the solution for LR equation. Kernel Linear Discriminant Classification (KLRC) is a non-linear extension of LRC, it helps to determine the kernel function. They have employed on three standard databases under some assessment protocols. This methodology not only out-performs the LRC and also it achieves a better performance than typical kernel approaches.

Ghinea et al. [17] have established a methodology to recognize the face images. Since, the image gradients are invariant to illumination and pose variations, the proposed applies gradient orientation to control the following effects. To extract the sub-space projection, Schur decomposition is applied for matrix decomposition as well as in both Schur-values and Schur-vectors. The respective sub-space projection is named as Schur-faces, which is numerically constant and has the capacity to handle defective matrices. To calculate the similarity measure between the numerous faces, the hausdorff distance is utilized with the nearby neighbor classifier. This experiment shows a promising accuracy for FR than the state-of-the-art methodologies.

3. PROPOSED METHODOLOGY

In proposed, the FR approach is utilized to analysis the human facial images by employing LRC algorithm, it exploits the fisher criterion on the discriminant sub-space. Fisher criterion improves the LRC algorithm as LDRC algorithm in order to increase the proportion of Between Class Reconstruction Error (BCRE) over Within Class Reconstruction Error (WCRE) for calculating the projection matrix (U) of LDRC.

3.1. Linear Discriminant Regression Classification (LDRC)

Training facial images of the $i-th$ class are stated as $C_i \in \Re^{S \times n_i}$, each column C_i is S dimensional to the facial images of class i. In which, the training images n_i are represented in vector as $i = 0, 1, 2, \ldots d$, where d is declared as the total number of classes. Considering, the probe face images P, which is denoted by utilizing C_i,

$$\begin{aligned} P &= C_i \beta_i, \\ i &= 0, 1, 2 \ldots d \end{aligned} \tag{1}$$

Where, $\beta_i \in \Re^{n_i \times 1}$ represented as regression parameter, β_i is determined by applying the least square estimation. In mathematically, it is specified as,

$$\begin{aligned} \hat{\beta}_i &= (C^T{}_i C_i) C^T{}_i P, \\ i &= 0, 1, 2, \ldots d \end{aligned} \tag{2}$$

Hence, the projected vector of parameters $\hat{\beta}_i$ with the predictor C_i is employed to determine the response vector of each class i, by equating the equations (2) and (1),

$$\begin{aligned} \hat{P}_i &= C_i \hat{\beta}_i \\ &= C_i (C^T{}_i C_i)^{-1} C^T{}_i P \\ &= H_i P, \\ i &= 0,1,2, \ldots d \end{aligned} \tag{3}$$

Where, H_i is stated as hat matrix, that plots P into $\hat{P}_i$. Finally, the RE of each class is determined and then LRC allocates the class P with lowest RE.

$$\begin{aligned} e_i &= \|P - \hat{P}_i\|^2{}_2, \\ i &= 0,1,2, \ldots d \end{aligned} \tag{4}$$

Feature extraction technique LDRC implements discriminant analysis in the LRC to provide effective discrimination, by employing labeled training data. Assuming, all the facial images from the matrix are denoted as $C = [C_1, \ldots C_i, \ldots, C_n] \in \Re^{S \times n}$, where n is characterized as the number of images and S is denoted as the dimension of images. Hence, the class label of C_i is declared as $l(C_i) \in \{0, 1, 2, \ldots d\}$. Considering, the sub-space projection matrix $U \in \Re^{S \times n}$ and each face images can be projected into the sub-space as,

$$U^* = \max_U \frac{tr(U^T \, BCREU)}{tr(U^T (WCRE + \in l) U)} \tag{5}$$

Where, $\in$ is symbolized as a positive number, l is an identity matrix and $tr(.)$ represents trace operator,

In case $n < S$, the label of P_i is similar to label of C_i and it is characterized as $l(P_i) \in l(C_i)$. The sub-space of projection matrix U is obtained by increasing BCRE and decreasing WCRE simultaneously, WCRE and BCRE are mathematically expressed as follows,

$$\text{WCRE} = \frac{1}{n}\sum_{i=1}^{n}(\text{C}_i - \text{C}_i^{\text{intra}})(\text{C}_i - \text{C}_i^{\text{intra}})^{\text{T}} \tag{6}$$

$$\text{BCRE} = \frac{1}{n(d-1)}\sum_{i=1}^{n}\sum_{j=1\, j\neq l(\text{C}_i)}^{d}(\text{C}_i - \text{C}_{ij}^{\text{inter}})(\text{C}_i - \text{C}_{ij}^{\text{inter}})^{\text{T}} \tag{7}$$

Where, $\text{C}_{ij}^{\text{inter}}$ is denoted as the RE of C_i and $l(\text{C}_i) \neq \text{J}$, $\text{C}_i^{\text{intra}}$ is characterized as the RE of C_i (C_i is emitted from the training matrix, while determining reconstruction).

3.2. Linear Collaborative Discriminant Regression Classification (LCDRC)

The following section describes, how the large class-specific BCRE domination issue can be diminished by the collaborative representation. In LCDRC, the WC features are compared with the total number of classes *d* features. While comparing, the ratio of distance between the classes are extremely maximized and also significantly reduce the distance of with in class features. In WCRE, individual features of the class are compensate with the *d* number of class features. Finally, the association between the WCRE and CBCRE can be denoted as,

$$\text{WCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n}\left\|\text{U}^{\text{T}}\text{C}_{ij} - \text{U}^{\text{T}}\text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right\|_2^2 \tag{8}$$

$$\text{CBCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n}\left\|\text{U}^{\text{T}}\text{C}_{ij} - \text{U}^{\text{T}}\text{C}_{ij}^{\text{inter}}\,\beta_{ij}^{\text{inter}}\right\|_2^2 \tag{9}$$

The respective equations (8) and (9) can be further re-written as follows,

$$\text{WCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)^{\text{T}}\text{UU}^{\text{T}}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)^{\text{T}} \tag{10}$$

$$\text{CBCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\beta_{ij}^{\text{inter}}\right)^{\text{T}}\text{UU}^{\text{T}}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\,\beta_{ij}^{\text{inter}}\right)^{\text{T}} \tag{11}$$

In the both CBCRE & WCRE have the factor of $1/n$, therefore, it is safe to eliminate $1/n$ from CBCRE & WCRE simultaneously without disturbing the value of CBCRE over WCRE. Under some algebraic deduction, CBCRE & WCRE can be denoted as follows,

$$\text{WCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n} tr\left(\text{U}^{\text{T}}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)^{\text{T}}\text{U}\right) \tag{12}$$

$$\text{CBCRE} = \sum_{i=1}^{d}\sum_{j=1}^{n} tr\left(\text{U}^{\text{T}}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\beta_{ij}^{\text{inter}}\right)\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\beta_{ij}^{\text{inter}}\right)^{\text{T}}\text{U}\right) \tag{13}$$

Where tr(·) is symbolized as the trace operator, eventually the following WCRE and BCRE can be denoted as follows,

$$\text{WCRE} = \frac{1}{n}\sum_{i=1}^{d}\sum_{j=1}^{n}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)\left(\text{C}_{ij} - \text{C}_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)^{\text{T}} \tag{14}$$

$$\text{CBCRE} = \frac{1}{n}\sum_{i=1}^{d}\sum_{j=1}^{n}\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\,\beta_{ij}^{\text{inter}}\right)\left(\text{C}_{ij} - \text{C}_{ij}^{\text{inter}}\,\beta_{ij}^{\text{inter}}\right)^{\text{T}} \tag{15}$$

3.3. Robust-LCDRC (RLCDRC)

In RLCDRC, the data samples are utilized in an effective manner. In order to illustrate the contribution of samples C_i to its own class, by employing a penalty function. Generally, the samples from the similar class has high intra-class RE, to limit the RE, a penalty $f(i)$ should be enforced. In mathematically, the penalty is determined as,

$$f(i) \;=\; \|C_i - C_i^{\text{intra}}\|^{-t_1} \tag{16}$$

Where, $C_i - C_i^{\text{intra}}$ is determined as the Euclidean distance between C_i and its intra-class RE vector, $t_1 > 0$ represented as tuning parameter.

Here, the penalty function $f(i)$ is a monotone increasing function, which depends on the distance between C_i and its intra-class RE vector. Likewise, for the inter-class RE, a penalty function $g(i, j)$ is enforced, to determine the importance of C_i to the $j-th$ inter-class data samples ($j \neq l(C_i)$).

It specifies that $g(i, j)$ is a monotone decreasing function and it depends on the distance between C_i and $j-th$ inter-class data samples. In mathematically, $g(i, j)$ is mentioned as,

$$g(i, j) \;=\; \|C_i - C_{ij}^{\text{inter}}\|^{-t_2} \tag{17}$$

Where, $t_2 > 0$ is represented as tuning parameter, $C_i - C_{ij}^{\text{inter}}$ denoted as the Euclidean distance between C_i and inter-class RE vector. Substitute, the two penalty functions in the respective equations (14) and (15),

$$\text{WCRE} \;=\; \frac{1}{n}\sum_{i=1}^{d}\sum_{j=1}^{n} f(i)\left(C_{ij} - C_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)\left(C_{ij} - C_{ij}^{\text{intra}}\,\beta_{ij}^{\text{intra}}\right)^{T} \tag{18}$$

$$\text{CBCRE} \;=\; \frac{1}{n}\sum_{i=1}^{d}\sum_{j=1}^{n} g(i, j)\left(C_{ij} - C_{ij}^{\text{inter}}\beta_{ij}^{\text{inter}}\right)\left(C_{ij} - C_{ij}^{\text{inter}}\,\beta_{ij}^{\text{inter}}\right)^{T} \tag{19}$$

The objective function of the RLCDRC is obtain, by substituting WCRE and BCRE in the equation (5),

$$U_{\text{RLCDRC}} \;=\; \max_{U}\frac{tr(U^{T}\,\overline{\text{CBCREU}}}{tr(U^{T}\;(\overline{\text{WCRE}} + \in I)U)} \tag{20}$$

To obtain the optimal matrix of $U_{\text{RLCDRC}} = (U_1, U_2, \ldots \ldots \ldots U_d)$, by solving the respective comprehensive eigen value concern,

$$\overline{\text{CBCRE}}\;U_K \;=\; \gamma(\overline{\text{WCRE}} + \in I)U_K$$

$$K \;=\; 1,2, \ldots d$$

Where, $$\gamma_1 \;\geq\; \ldots \gamma_K \ldots \gamma d.$$

4. EXPERIMENTAL RESULT AND DISCUSSION

In this section, the experimental outcome is described in detailed, which is implemented in PC with 1.8GHz Pentium IV processor using MATLAB (version 6.5). To evaluate the effectiveness of proposed algorithm, the performance of LCDRC is compared with RLCDRC on the reputed face database sets like (ORL, YALE B, and Extended YALE B). In our experiment, all the facial images are cropped at the size of $^{32 \times 32}$.

4.1. Result for ORL Database

The ORL facial database set holds 400 face images with 40 individuals, each individual contains 10 face images respectively. Here, the following face images are taken under numerous facial expressions and altered lightening conditions, the sample face images of ORL database is given below in figure 1.

Figure 1: ORL facial Database set

The performance of LCDRC and the proposed RLCDRC in ORL database is determined and compared by referring the following figures 2, 3, 4, and 5. The effective recognition rate and the corresponding feature dimensions are given in four various training classes. All the training classes confirms that the proposed scheme is very effective in nature.

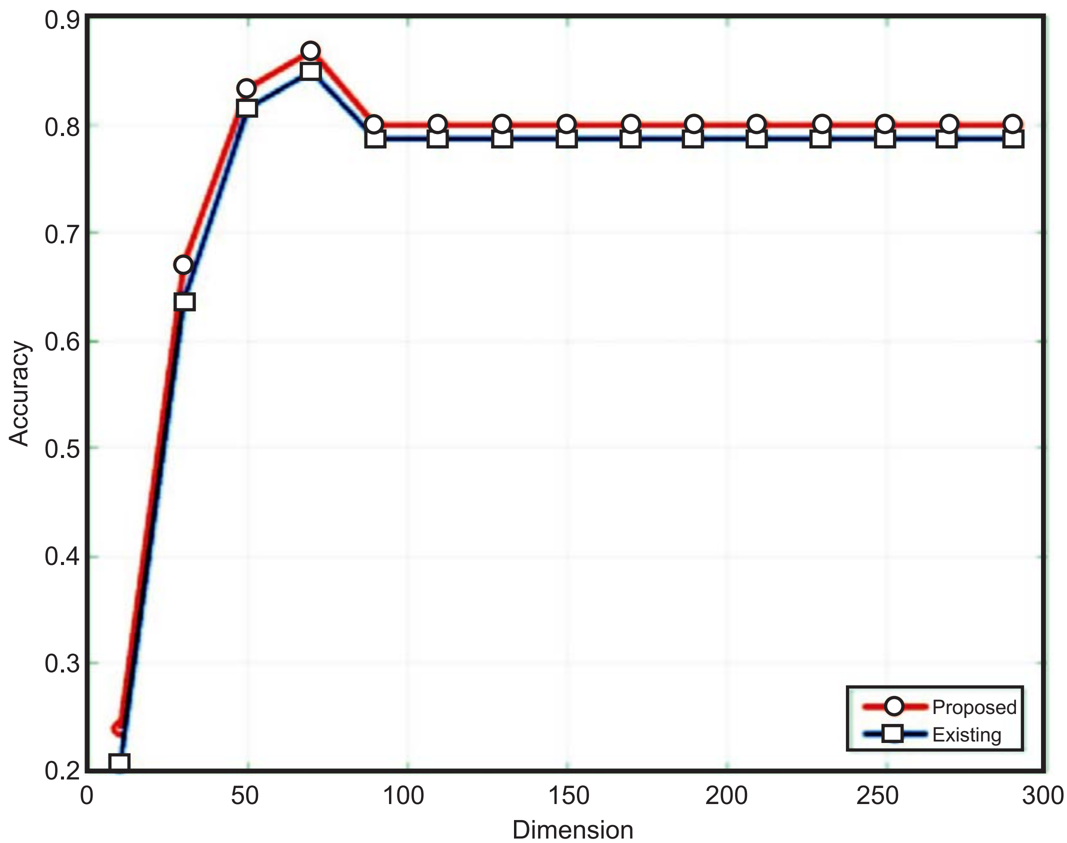

Figure 2: Two train (dimension vs Accuracy)

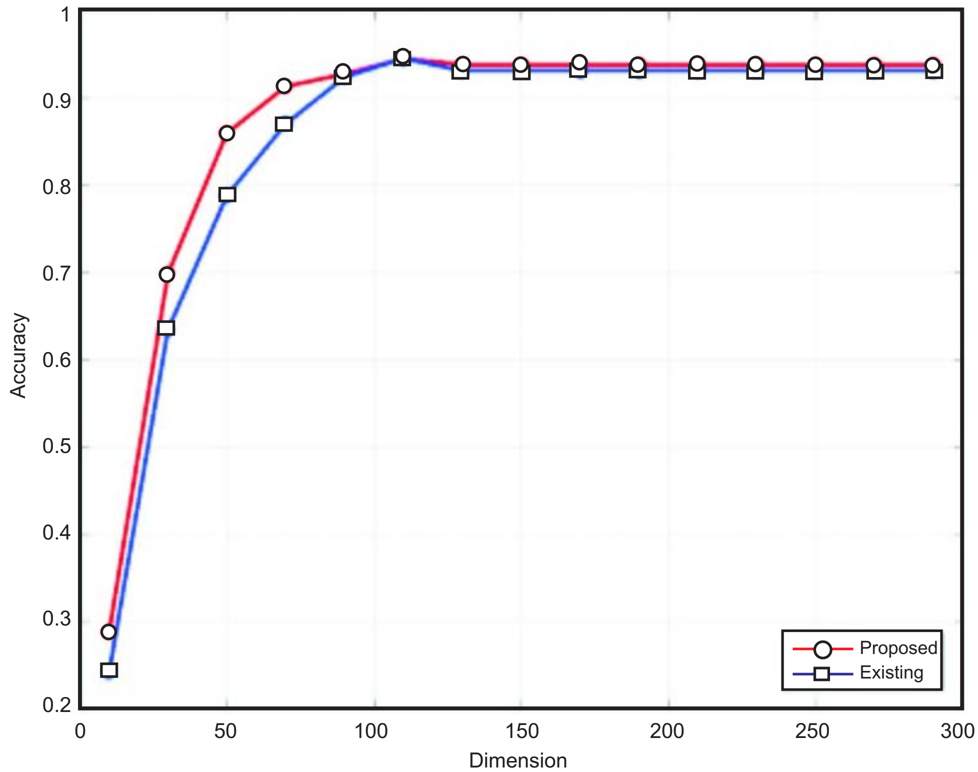

Figure 3: Three train (dimension vs Accuracy)

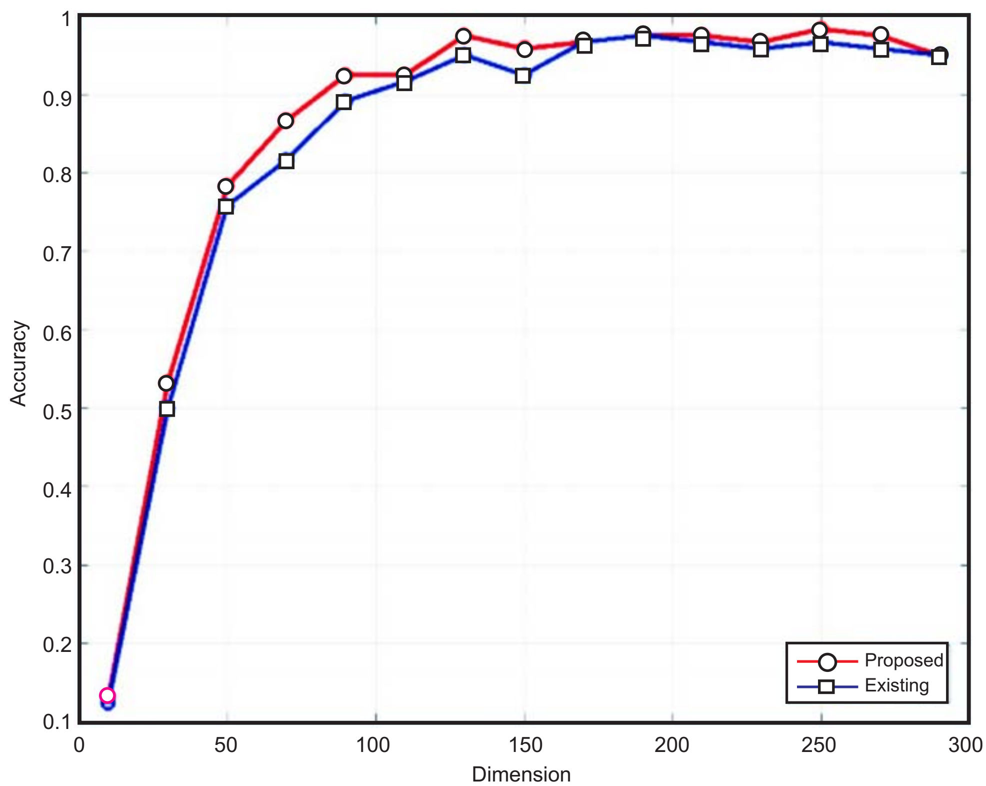

Figure 4: Seven train (dimension vs Accuracy)

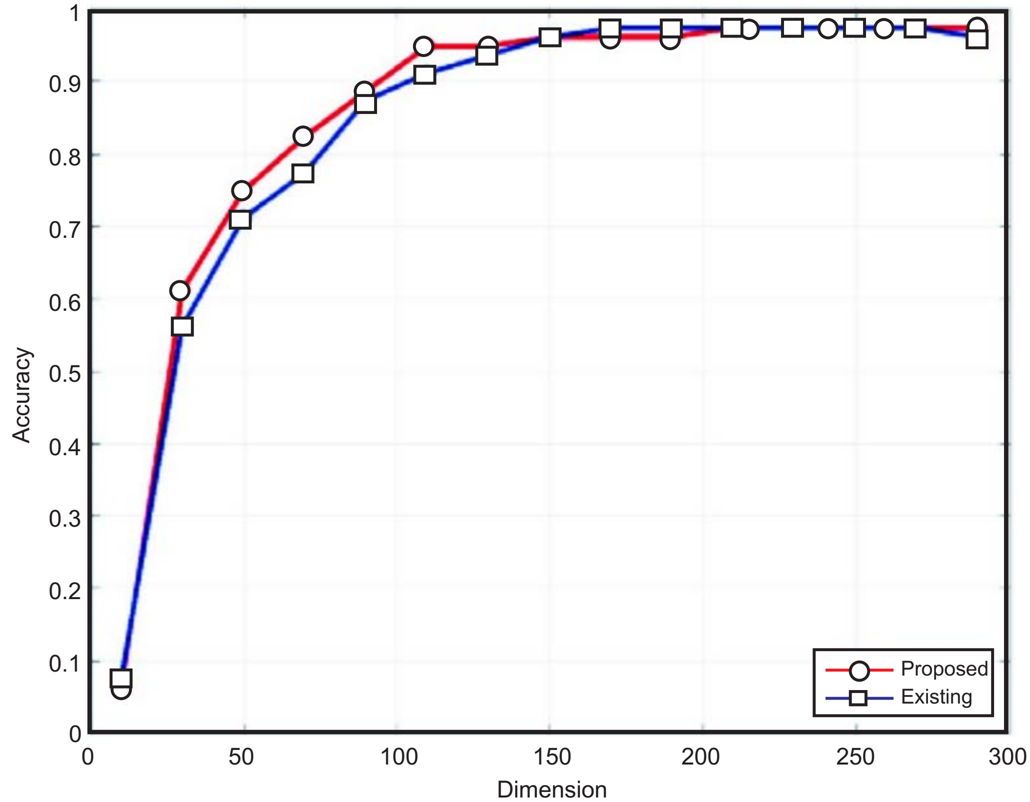

Figure 5: Eight train (dimension vs Accuracy)

4.2. Result for YALE B Database

Normally, YALE B face database contains 15 individuals with 165 face images, each individuals holds 11 facial images under altered configurations and with different facial expressions, the sample face images of YALE B database is mentioned in figure 6.

Figure 6: YALE B Face Database

The performance of LCDRC and the proposed RLCDRC in YALE B database is determined and compared by referring the following figures 7, 8, 9, and 10. For example, the significant recognition rate and the corresponding feature dimensions are mentioned in four various training classes. By analyzing all the training classes, the proposed approach shows a significant outcome in FR.

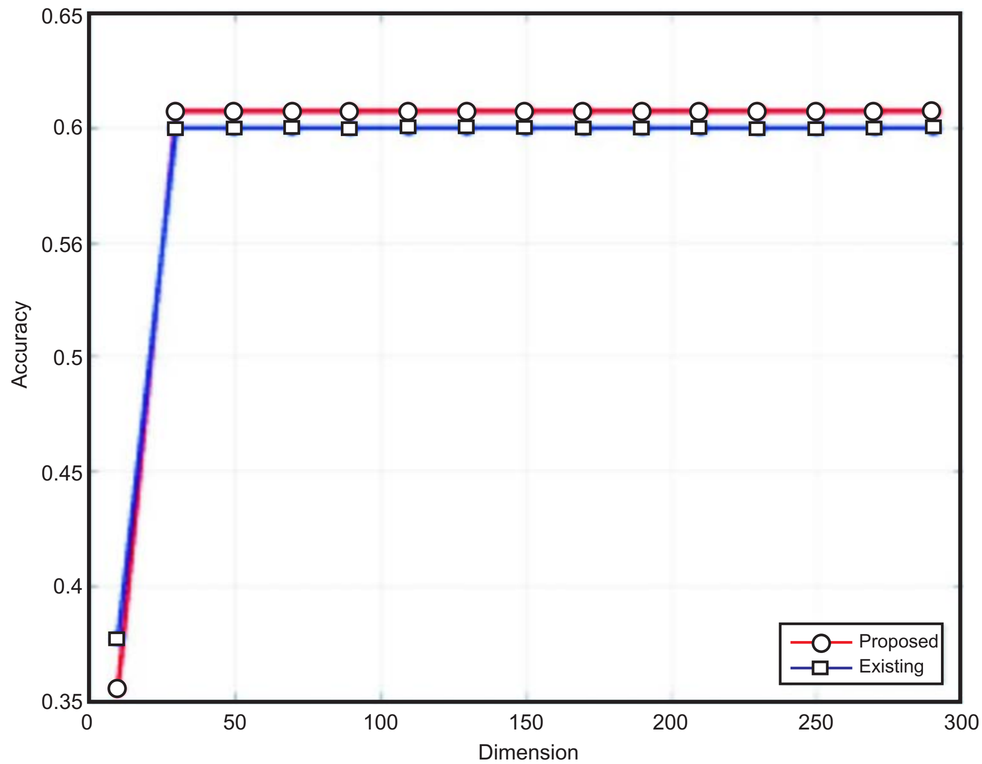

Figure 7: Two train (dimension vs Accuracy)

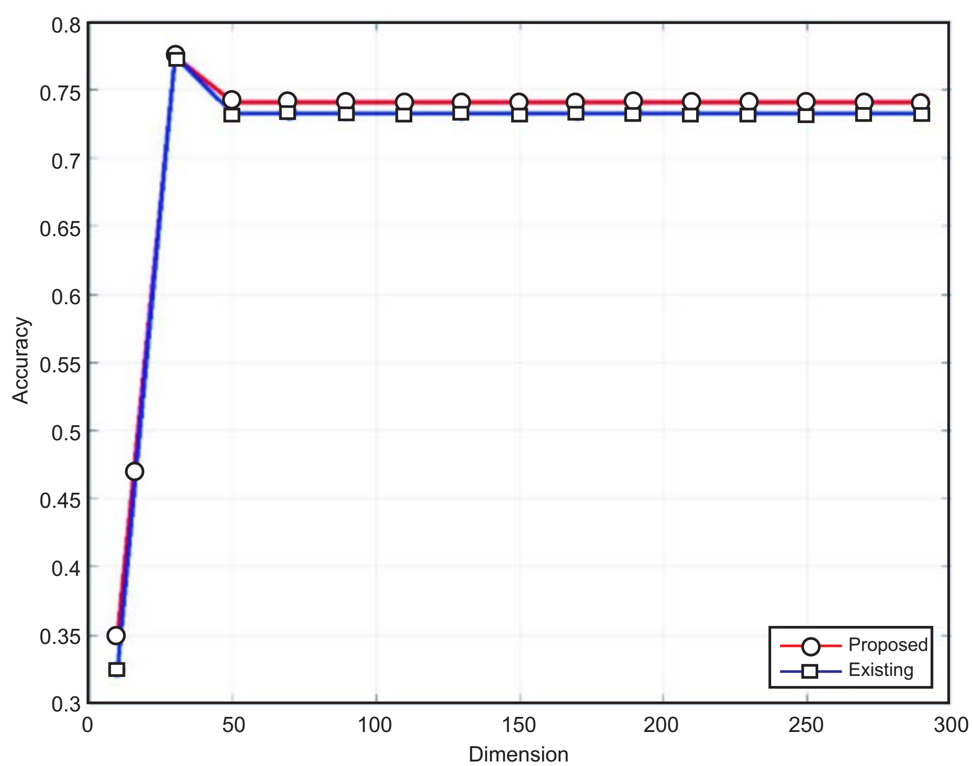

Figure 8: Three train (dimension vs Accuracy)

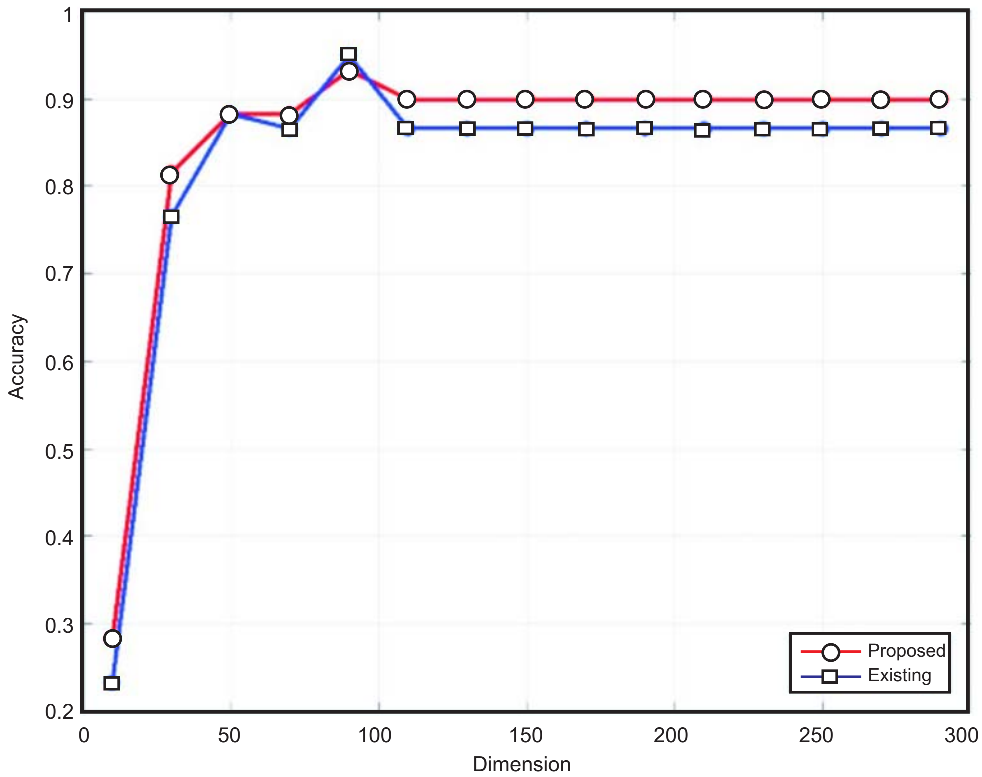

Figure 9: Seven train (dimension vs Accuracy)

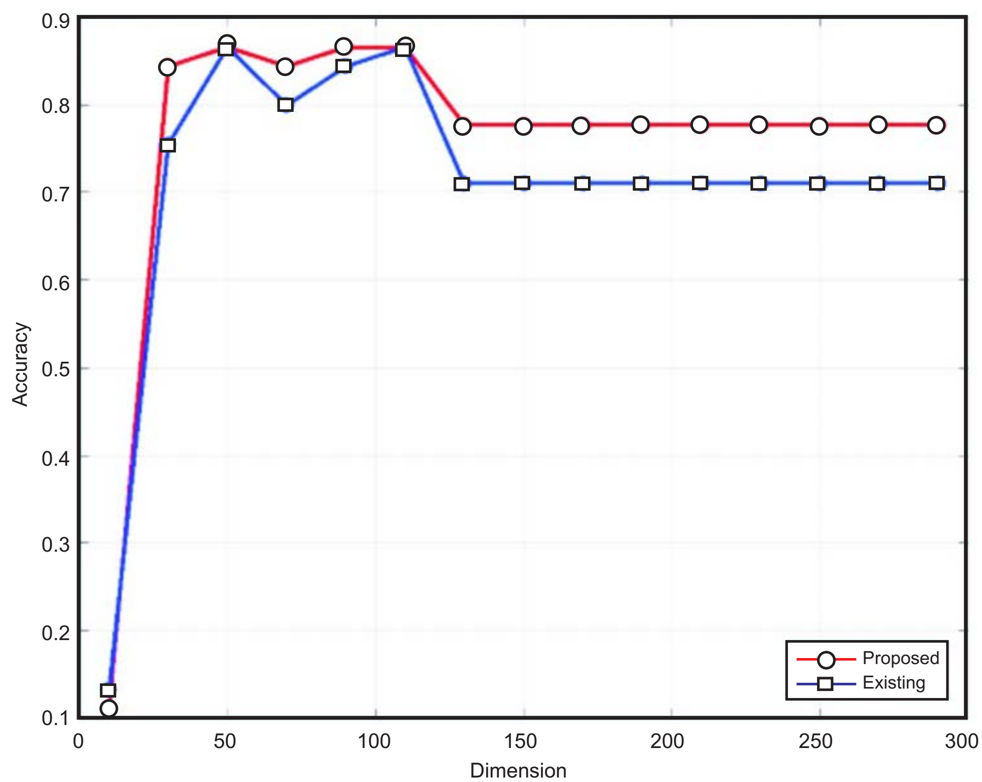

Figure 10: Eight train (dimension vs Accuracy)

4.3. Result for Extended YALE B Database

In this section, the extended YALE B database consists of 11 individuals with 16128 facial images, each individuals contains 10 facial images under different configurations and with altered facial expressions, the sample face images of Extended YALE B database is represented in the below figure 11.

Figure 11: Extended YALE B Face Database

The performance of LCDRC and the proposed RLCDRC in Extended YALE B database is determined and compared by referring the following figures 12, 13, 14, and 15. For instant, the best recognition rate and the corresponding feature dimensions are detailed in four different training classes with superior results.

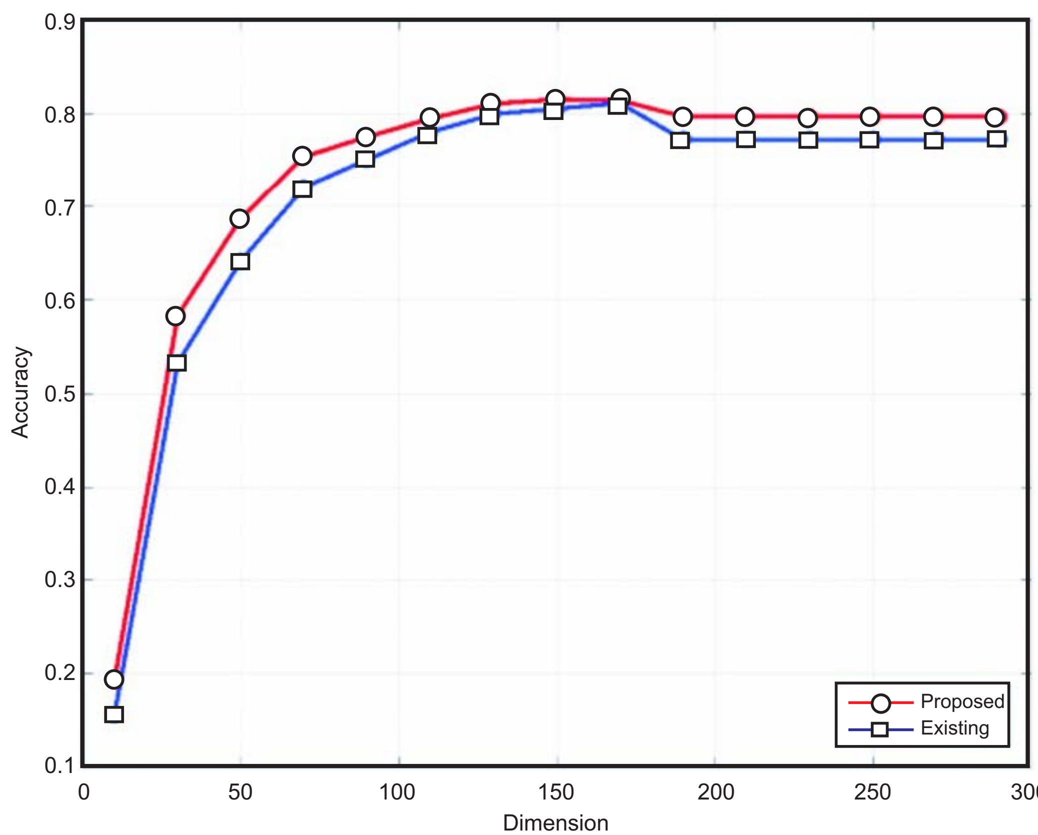

Figure 12: Five train (dimension vs Accuracy)

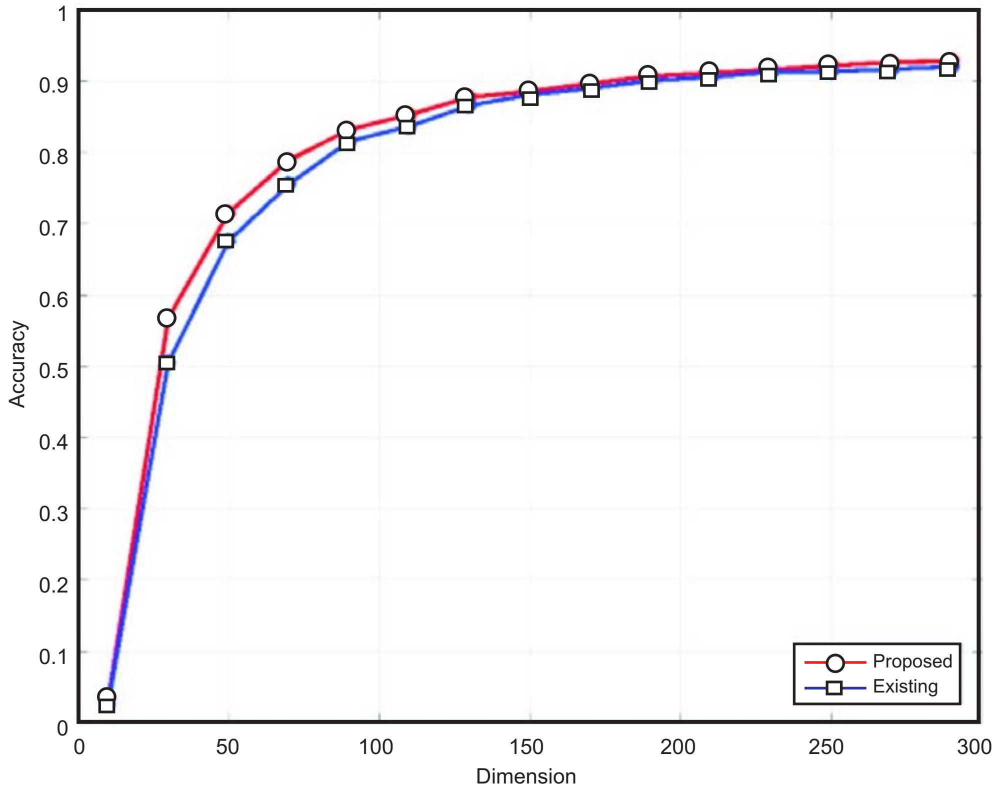

Figure 13: Ten train (dimension vs Accuracy)

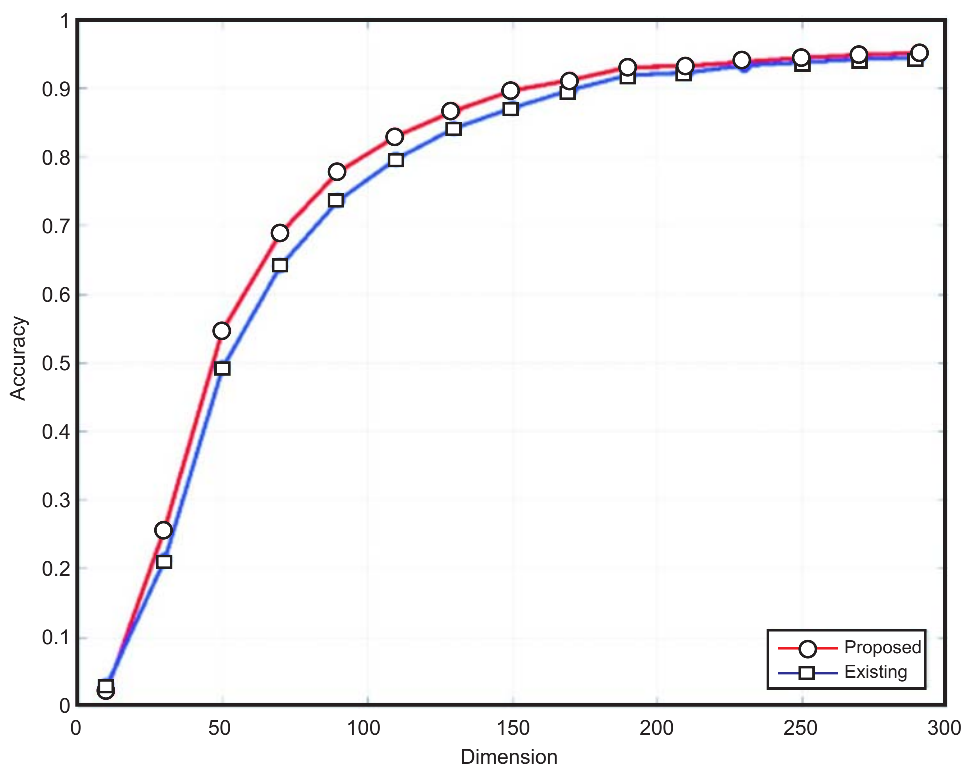

Figure 14: Twenty train (dimension vs Accuracy)

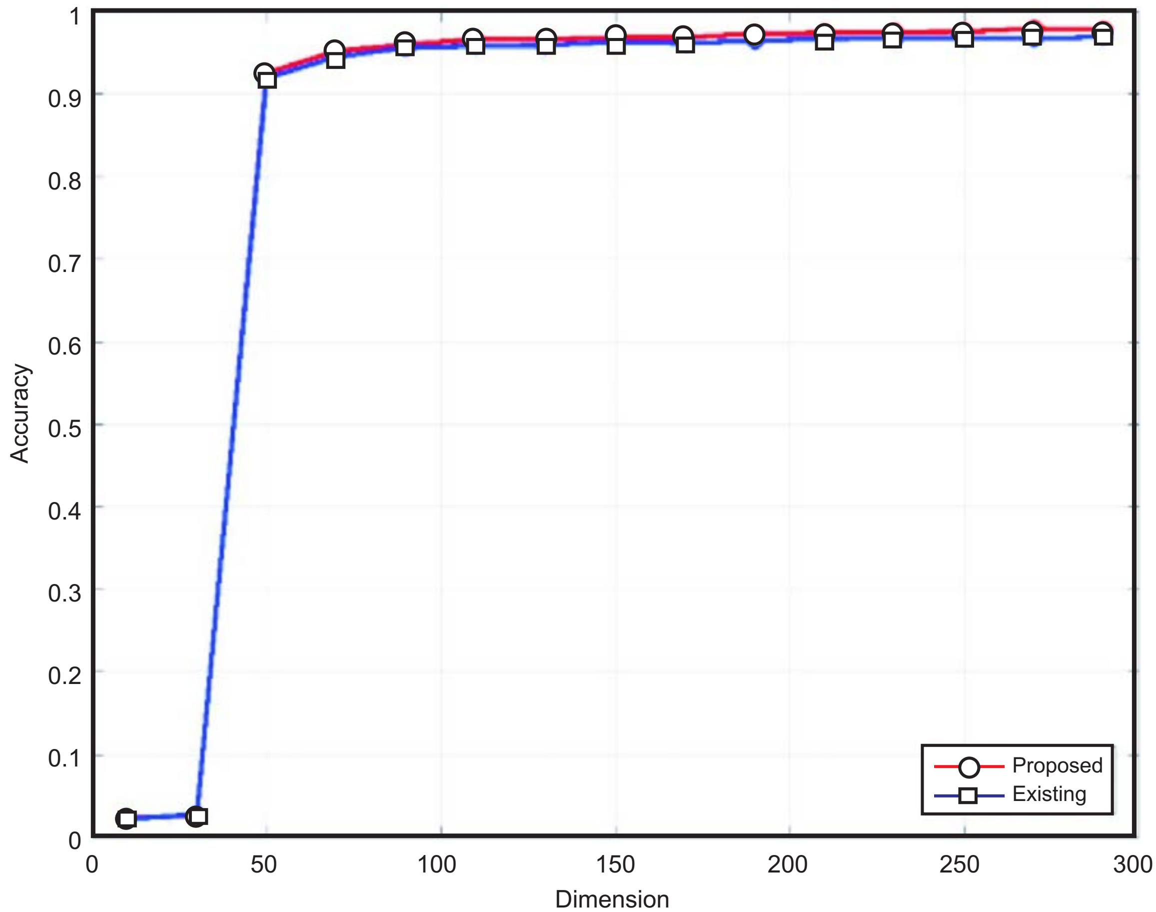

Figure 15: Thirty train (dimension vs Accuracy)

The following Table.1 and Table. 2 indicates the performance analysis of RLCDRC over LCDRC for three different database sets.

Table 1
Performance evaluation table for ORL and YALE B database

	Facial Database	*Two training Accuracy*	*Three training Accuracy*	*Four training Accuracy*	*Five training Accuracy*	*Six training Accuracy*	*Seven training Accuracy*	*Eight training Accuracy*
ORL	LCDRC	85	94.64	87.95	91	95.63	97.5	94.56
	Proposed RLCDRC	86.88	94.64	88.12	92.60	96.25	98.33	97.60
YALE B	LCDRC	60	77.5	78.10	86.67	79.70	95	82
	Proposed RLCDRC	60.74	77.5	79.05	85.56	78.84	93.33	84.45

Table 2
Performance evaluation table for Extended YALE B database

	Facial Database	*Five training Accuracy*	*Ten training Accuracy*	*Twenty training Accuracy*	*Thirty training Accuracy*	*Forty training Accuracy*	*Fifty training Accuracy*
LCDRC	Extended YALE B	81.16	92.13	94.62	87.69	93.5	90.87
Proposed RLCDRC	Extended YALE B	81.56	92.92	95.28	86.45	94.76	91.20

5. CONCLUSION

In this scenario, a new discriminant analysis scheme named as RLCDRC, which is established for extracting the feature and FR. Here, the proposed RLCDRC method is an improved version of LCDRC and traditional LDRC that helps to maximize the value of BCRE and minimize the value of WCRE, which result in an optimum projection matrix. The following experiment verified on a few databases (ORL, YALE B, and Extended YALE B) that shows a superiority of the proposed scheme. The recognition rate on the sub-space is more significant in RLCDRC than the other traditional techniques.

REFRENCES

[1] Y. Bi, M. Lv, Y. Wei, N. Guan, and W. Yi, “Multi-feature fusion for thermal face recognition”, *Infrared Physics & Technology*, Vol. 77, 2016 pp. 366-374.

[2] Z.R. Lai, D.Q. Dai, C.X. Ren, and K.K. Huang, “Discriminative and compact coding for robust face recognition”, *IEEE transactions on cybernetics*, Vol. 45, No. 9, 2015, pp. 1900-1912.

[3] L. Pishchulin, T. Gass, P. Dreuw, and H. Ney, “Image warping for face recognition: From local optimality towards global optimization”, *Pattern Recognition*, Vol. 45, No. 9, 2012, pp. 3131-3140.

[4] A. Yao, and S. Yu, “Robust face representation using hybrid spatial feature interdependence matrix”, *IEEE Transactions on Image Processing*, Vol. 22, No. 8, 2013, pp. 3247-3259.

[5] L. Tian, C. Fan, and Y. Ming, “Learning iterative quantization binary codes for face recognition”, *Neurocomputing*, Vol. 214, 2016, pp. 629-642.

[6] Y.L. Liu, D.R. Zhu, D.X. Zhang, and F. Liu, “A linear regression based face recognition method by extending probe images”, *Optik-International Journal for Light and Electron Optics*, Vol. 126, No. 22, 2015, pp. 3335-3339.

[7] J. Lu, Y.P. Tan, G. Wang, and G. Yang, “Image-to-set face recognition using locality repulsion projections and sparse reconstruction-based similarity measure”, *IEEE transactions on circuits and systems for video technology*, Vol. 23, No. 6, 2013, pp. 1070-1080.

[8] C. Yang, C. Liu, N. Wu, X. Wu, Y. Li, and Z. Wang, “Collaborative representation with reduced residual for face recognition”, *Neural Computing and Applications*, Vol. 25, No. 7-8, 2014, pp. 1741-1754.

[9] N. Piao, and R.H. Park, “Face Recognition Using Dual Difference Regression Classification”, *IEEE Signal Processing Letters*, Vol. 22, No. 12, 2015, pp. 2455-2458.

[10] H.S. Du, Q.P. Hu, D.F. Qiao, and I. Pitas, “Robust face recognition via low-rank sparse representation-based classification”, *International Journal of Automation and Computing*, Vol. 12, No. 6, pp. 579-587.

[11] X. Qu, S. Kim, R. Cui, and H.J. Kim, “Linear collaborative discriminant regression classification for face recognition”, *Journal of Visual Communication and Image Representation*, Vol. 31, 2015, pp.312-319.

[12] H. Li, and C.Y. Suen, "Robust face recognition based on dynamic rank representation", *Pattern Recognition*, Vol. 60, 2016, pp.13-24.

[13] S.B. Chen, C.H. Ding, and B. Luo, "Extended linear regression for undersampled face recognition", *Journal of Visual Communication and Image Representation*, Vol. 25, No. 7, 2014, pp. 1800-1809.

[14] X. Song, X. Yang, C. Shao, and J. Yang, "Parity symmetrical collaborative representation-based classification for face recognition", *International Journal of Machine Learning and Cybernetics*, pp.1-8.

[15] Z. Lu, X. Jiang, and A.C. Kot, "A color channel fusion approach for face recognition", *IEEE Signal Processing Letters*, Vol. 22, No. 11, 2015, pp. 1839-1843.

[16] Y. Lu, X. Fang, and B. Xie, "Kernel linear regression for face recognition", *Neural Computing and Applications*, Vol. 24, No. 7-8, 2014, pp.1843-1849.

[17] G. Ghinea, R. Kannan, and S. Kannaiyan, "Gradient-orientation-based PCA subspace for novel face recognition", *IEEE Access*, Vol. 2, 2014, pp. 914-920.