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Improved Face Recognition using a Modified PSO Based Self-Weighted Linear Collaborative Discriminant Regression Classification

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Abstract: Biometric authentication utilizing Face Recognition (FR) is emerging as a significant research field. In this scenario, Linear Collaborative Discriminant Regression Classification (LCDRC) scheme is undertaken for experimental examination. Whereas, LCDRC could not able to categorize the samples that scattered around the intersections and also it gives a poor outcome in severe lighting variations. In order to overcome this difficulties, an effective weight function along with Deep Learning (DL) is included in LCDRC. Respective weight function is selected based on Modified-Particle Swarm Optimization (MPSO) algorithm. This proposed methodology significantly maximize the Reconstruction Error (RE) between the classes and also it minimize the RE within the class. Though, the proposed methodology not only out-performs LCDRC, also it provides superior outcome in terms of accuracy.

Key words: Deep learning, face recognition, linear collaborative discriminant regression classification, modified particle swarm optimization, reconstruction error

INTRODUCTION

FR is the most successive strategy that involves in the co-ordination of several applications in computer vision technology as it provides an identity to all individuals effectively (Lu *et al.,* 2014). The human ability of recognizing and identifying a face is naturally effective as human can memorize more than thousands of faces in their brain but it may not be accurate all the time. The brain can fail to decode some of the faces due to viewing condition, diversion in expression or some distractions (Paul and Al-Sumam, 2012; Bhattacharyya and Rahul, 2013). Thus, the automatic face analysis technique has created an attention among research community due to its various functional applications. It is the process of analyzing the static or even moving people from natural scenes or public places in particular which requires a set of visual mission to be performed strongly.

Generally, FR is the most prominent technology found in the domain of biometric authentication which is the important technique used in identifying and authorizing a person. Face images are progressively utilized additional means for validation in uses of high security zone. There are numerous search algorithms and techniques are available in FR (Vyas and Garg, 2012).

Neural networks, Linear Discriminant Analysis (LDA), Fuzzy logic are some of the methodologies utilized to perform biometric face authentication process (Philips, 1999; Chen *et al.*, 2014). These methods shave some issue to differentiate or recognize various persons by their face features, because all may not contain same series of features and appearances. LDA is a superior method illustrated to perform classification of face images in FR method which gives a satisfactory result than the other systems (Chu *et al.,* 2015; Luan *et al.*, 2014). LDA attempts to model dissimilarity between the classes containing explicit data and it is a powerful method used for recognizing the face that satisfies the challenges noticed in conventional techniques with the application of linear discriminant factor (Viswanathan and Viswanathan, 2016; Huang and Yang, 2013). The performance of LDA is improved by including the discriminant analysis criterion into linear regression classification which is mentioned as Linear Discriminant Regression Classification (LDRC) that helps to enhance the grade of performance created by LDA. Many researchers have developed various innovations in improvising the LDRC methodology to project more successive applications.

In this study, the Self-Weighted-LCDRC (SW-LCDRC) is introduced with the inclusion of deep learning

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approach. This method involve in producing an improved dimensionality reduction from which the classification algorithm extracts the efficient features to make the better classification accuracy. Whereas, the self-weighted function is selected by employing modified-PSO which makes the SW-LCDRC algorithm fast and accurate.

Literature review: Jin *et al.* (2016) have illustrated a new Extreme Learning Machine (ELM) approach for cross-methodology confront matching. Proposed approach coordinated the Voting based ELM (V-ELM) with a novel learning based face descriptor. Initially, the discriminant feature learning was projected to study the cross-modality feature demonstration. Then, the subspace learning based technique was utilized to diminish the attained cross-modality features. At last, Voting-ELM was utilized as the classifier to improve the exactness and to accelerate the component learning procedure. Experiments on three Heterogeneous-FR (HFR) applications demonstrated the viability and speculation of the proposed strategy. Whereas, ELM showed limited outcome in unreadable images due to high illumination and pose variation.

Liu *et al.* (2015) have presented a linear regression based approach for generating the low dimensional features for down sampling. In addition, the virtual samples were summed up with down sampling. This stage was to categorize the probe by using canonical correlation analysis. Also, the comparison of recognition rate between this method and other classification method was presented in this literature. The classification decision has been made for the class which has the highest correlation with the probe set. The experiment on two face datasets pointed out the better performance of this technique for low dimensional features. This literature study didn't focused on high dimensional features for sampling.

Huang *et al.* (2016) proposed an Adaptive-LDRC (A-LDRC) algorithm for different contributions of the training samples. Specially, ALDRC utilize different weights to classify the different contributions of the training samples and use the weighting information to measure the Between-Class Reconstruction Errors (BCRE) and Within-Class Reconstruction Errors (WCRE). Then, ALDRC identified an optimal projection matrix which can increase the ratio of BCRE over WCRE. Experiments validated on the ORL, AR and FERET face databases determined the efficiency of the projected methodology.

Cheng *et al.* (2016) projected an enhanced Collaborative Representation based Classification (CRC) technique. At first, the image Gabor features were extracted and utilized to create preliminary dictionary. At the second stage, CRC learn discriminative dictionary by a Label Consistent K-SVD (LC-KSVD) technique which merges the sparse coding error with the RE and the classification error. At last, l2-norm of coding residual in CRC-RLS was calculated and then the classification problem was changed into solving linear programming problem. Experimentation on two benchmark face databases with variation of illumination, expression and occlusion demonstrated that the proposed technique can get high classification precision with limited time-consuming but it is applicable only for smaller size database. To overcome the before mentioned drawbacks, an effective methodology is implemented in LCDRC which enhances, the procedure acclimated in our anticipated strategy.

MATERIALS AND METHODS

In this scenario, the FR is examined by utilizing LCDRC algorithm which exploits the fisher criterion on discriminant sub-space. Whereas, the fisher criterion improves the proportion of BCRE over WCRE for calculating the projection matrix U of LCDRC. Projection matrix U delivers a significant outcome on both higher and lower dimension recognition rate.

Linear Collaborative Discriminant Regression Classification (LCDRC): Training facial images of the ith 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 characterized in vector as i = 0, 2, ..., d where, d is declared as the total number of classes. Considering, the probe face images P which is symbolized by employing C_i:

$$P = C_i \beta_i, i = 0, 1, 2, ..., d \quad (1)$$

Where, $\beta_i \in \Re^{n_i \times 1}$ signified as regression parameter β_i is evaluated by employing the least square estimation. Mathematically, β_i is represented as follows:

$$\hat{\beta}_i = \left(C_i^T C_i\right)^{-1} C_i^T P, i = 0, 1, 2, ..., d \quad (2)$$

Projected vector of parameters $\hat{\beta}_i$ with the predictor C_i is employed to calculate the response vector of each class i. Substitute the Eq. 1 and 2 in Eq. 3:

$$\hat{P}_i = C_i \hat{\beta}_i = C_i \left(C_i^T C_i\right)^{-1} C_i^T P = H_i P, i = 0, 1, 2, ..., d \quad (3)$$

Where, H_i is specified as hat matrix that plots P into $\hat{P}_i$. At last, the RE of each class is evaluated with lowest RE:

$$e_i = \| P - \hat{P}_i \|_2^2, i = 0, 1, 2, ..., d \quad (4)$$

Feature extraction method LCDRC implement discriminant analysis in the LRC to deliver effective discrimination. Assuming, all the facial images from the matrix are signified as:

$$C = [C_i, ..., C_i, ..., C_n] \in \Re^{S \times n}$$

Where:

n = The number of images
S = The dimension of images

Hence, the class label of C_i is stated as $l(C_i) \in \{0, 1, 2, ..., d\}$. In addition, the sub-space projection matrix $U \in \Re^{S \times n}$, $n < S$ is determined by mapping each C_{ij} into the learned sub-space.

$$P_{ij} \; U^T C_{ij} \text{ where, } 1 \le j \le n \quad (5)$$

Mapping of entire training face image matrix for each class is done to derive the linear discrimination function P_i equation, where, U_T is named as projection matrix for whole set and T represents the transformation of classes.

$$P_i = U^T C_i \in \Im^{S \times n} \quad (6)$$

Deep learning algorithm: DL is the strategy of learning multiple levels of illustration and abstraction which helps to sense the information like text, image, etc. In this examination, DL algorithm alters U projection matrix as memory matrix that significantly reduce the sematic gap between reference images and training images. This memory matrix in LCDRC helps to decrease the error occurred in the system and also enhance the performance of LCDRC. Additionally, the back propagation weight is employed by utilizing stochastic gradient descent as stated in the following equation:

$$U^{T*} = U^T + \eta \frac{\partial F}{\partial U} \quad (7)$$

Where:

η = Learning rate
$\eta \partial F / \partial U$ = Whole learning function
F = The cost function

Training images C_i from the class i are learned by using DL algorithm and the projection matrix form the linear discrimination function can be written as:

$$P_i = U^{T*} C_i \in \Im^{S \times n} \quad (8)$$

To identify an optimal solution of DL-LCDRC algorithm, it is essential to maximize the ratio of BCRE over WCRE which helps in motivating the DL-LCDRC for classification. Now, substitute Eq. 8 in Eq. 4. Then, the BCRE and WCRE are represented in inter-class and intra-class variances of the training samples that is presented in Eq. 9 and 10:

$$BCRE = \frac{1}{n} \sum_{i=1}^{d} \sum_{j=1}^{n} \left\| P_i - \hat{P}{}_{ij}^{r} \right\|_2^2 \quad (9)$$

$$WCRE = \frac{1}{n} \sum_{i=1}^{d} \sum_{j=1}^{n} \left\| P_i - \hat{P}{}_{ij}^{r} \right\|_2^2 \quad (10)$$

Where inter and intra-classes are projected by $\hat{P}{}_{ij}^{r} = P_{ij}^r \beta_{ij}^r$ and $\hat{P}{}_{ij}^{a} = P_{ij}^r \beta_{ij}^a$. Value P_{ij}^r signifies P with P_i eliminated and the value P_{ij}^a characterize with P_{ij} eliminated. Value β is unknown until the projection matrix is achieved. The value of β_{ij}^r and β_{ij}^a is attained from $\hat{\beta}_i = (C_i^T C_i)^{-1} C_i^T P, i = 0, 1, 2, ..., d$. For improving the low dimensional recognition rate, a self-weighting function is included in $\hat{\beta}_i$ which is symbolized in Eq. 2.

Self-weighting function: Let, the training facial images are considered as:

$$C_i^{w_j} = [C_{i1}^{wj}, C_{i2}^{wj}, ..., C_{iS}^{wj}]^T$$

where, (i = 0, 1, 2, ..., n_i), (j = 0, 1, 2, ..., d) be the S dimensional training sample class w_j, where, n_i is the number of samples and d is the number of classes. $n = \sum_{i=1}^{d} n_i$ is indicated by the total number of training samples. In order to measure the difference among features, the mean of total training samples of feature v is evaluated by:

$$m_v = \left(\frac{1}{n}\right) \sum_{i=1}^{n_i} \sum_{j=1}^{d} C_{iv}^{W_j}, \; (v = 1, ..., e)$$

And local mean of class W_j of feature:

$$u_v^{W_j} = \left(\frac{1}{n_i}\right) \sum_{i=1}^{n_i} C_{iv}^{W_j}$$

The way to estimate the weights of features is adapted from LCDRC, the between-class variance Z_v^B of the feature v which is defined by the following formulation:

$$Z_v^B = \frac{1}{d} \sum_{i=1}^{d} \left(m_v - u_v^{w_j}\right)\left(m_v - u_v^{w_j}\right), v = 1, ..., e \quad (11)$$

Similarly, the within class variance Z_v^W of the feature v is computed by:

$$Z_v^W = \sum_{j=1}^{d} U_j Z_{jv}, v = 1, ..., e \quad (12)$$

Where:

$U_j = \frac{n_i}{n}$ = The prior probability of class w_j

Z_{jv} = The variance of class w_j of feature v

Finally, the weighting feature f_v is according to the ratio of the between-class variance z_v^B to the within-class variance z_v^W that is given in Eq. 13:

$$f_v = \frac{Z_v^B}{Z_v^W}, v = 1, ..., e \quad (13)$$

It is apparently that this metric is based on LCDRC but with some modification. After including the self-weighting function f_v in the Eq. 2 which is represented as follows:

$$\hat{\beta}_i = \left(C_i^T C_i + f_v I\right)^{-1} C_i^T P, i = 0, 1, 2, ..., d \quad (14)$$

Where:

I = The sated as identity matrix

$\hat{\beta}$ = The original space and useas an $\hat{\beta}$ approximation of β

Then, the projection matrix $U \in \Im^{S \times n}$ can be learned from the minimized equation of inter and intra class variances. According to the relationships between C and P, BCRE and WCRE can be rewriter as follows:

$$BCRE = \sum_{i=1}^{d}\sum_{j=1}^{n}\left(x_i - C_{ij}^r \beta_{ij}^r\right)^T UU^T \left(x_i - C_{ij}^r \beta_{ij}^r\right) \quad (15)$$

$$WCRE = \sum_{j=1}^{n}\left(x_i - C_{ij}^a \beta_{ij}^a\right)^T UU^T \left(x_i - C_{ij}^a \beta_{ij}^a\right) \quad (16)$$

Factor 1/n in both the equation of BCRE and WCRE should be eliminated and compressed as it may affect the ratio of the equation which can be done by adding a trace operator tr(.) and the variables α_b and α_w with an algebraic deduction as:

$$BCRE = tr\left(U^T \alpha_b U\right) \quad (17)$$

$$WCRE = tr\left(U^T \alpha_w U\right) \quad (18)$$

Where:

$$\alpha_b = \sum_{i=1}^{d}\sum_{j=1}^{n}\left(x_i - C_{ij}^r \beta_{ij}^r\right)^T \left(x_i - C_{ij}^r \beta_{ij}^r\right) \quad (19)$$

$$\alpha_w = \sum_{j=1}^{n}\left(x_i - C_{ij}^a \beta_{ij}^a\right)^T \left(x_i - C_{ij}^a \beta_{ij}^a\right) \quad (20)$$

Equation 19 and 20 show the simplified form of Linear regression Eq. 17 and 18 for the proposed algorithm. The BCRE and WCRE are further maximized simultaneously by adopting the Maximum Margin Criterion (MMC) which can be denoted as J(U):

$$\begin{aligned} \max_U J(U) &= \max_U(\text{BCRE-WCRE}) \\ \max_U J(U) &= \max_U\left(tr\left(U^T\left(\alpha_b - \alpha_w\right)U\right)\right) \end{aligned} \quad (21)$$

Equation 21 can be solved by finding the largest d eigenvalues and the according eigenvectors as the following:

$$\left(\alpha_b - \alpha_W\right)u_k = \lambda_k u_k \quad (22)$$

From the Eq. 22, $\lambda_1 \geq, ..., \lambda_k, ..., \geq \lambda_d$ and $U = [U_1, ..., U_k, ..., U_d]$. MMC can solve the Small Sample Size Problem (SSSP). Where, the dimension of the face image is larger than the number of training face images. Lagrange multipliers λ_k is optimized by the LCDRC algorithm as:

$$\lambda_k = \eta_f \lambda_k 1 \leq k \geq d \quad (23)$$

Where, η_f is considered as final rate. Though, f_v generates weight value for each iteration with respect to z_v^B and z_v^B. In order to determine the global best optimum weight value, an effective algorithm was implemented named as Modified-Particle Swarm Optimization (M-PSO) algorithm.

Modified particle swarm optimization: This study discussed about a new learning strategy named PSO. Here, PSO concentrates on three main components such as personal best experience, global best experience and the worst experience of the particles i. In PSO, the particle i is spread in a dimensional space S. Each particle i is associated with respective position and velocity.

In current state, the velocity vector of particle is denoted as $a_i = [a_{i1}, a_{i2}, ..., a_{is}]$ and the position vector is denoted as $b_i = [b_{i1}, b_{i2}, ..., b_{is}]$. Moreover, each particle has historically best position vector $a_i = [h_{i1}, h_{i2}, ..., h_{is}]$. The best position of the particle i depends on the position of neighborhood particles $a_i = [N_{i1}, N_{i2}, ..., N_{is}]$. The vectors a_i and b_i are modified randomly and updated in the following Eq. 24 and 25. In order to find the new velocity and position of the particle i:

$$a_{iS} = wa_{iS} + c_1 r_{1s}\left(h_{is} - b_{is}\right) + c_2 r_{2s}\left(N_{is} - b_{is}\right) \quad (24)$$

Where, w is the inertia weight that is used to control the exploitation and exploration capabilities of the algorithm. Parameters c_1 and c_2 are acceleration co-efficient, r_{1s} and r_{2s} are the two randomly generated values within the range of [0, 1] in the S dimensional space.

RESULTS AND DISCUSSION

Experimental analysis: In this scenario, the experimental outcome was implemented in PC with 1.8 GHz Pentium IV processor utilizing MATLAB (Version 6.5). In order to estimate the efficiency of proposed algorithm, the performance of LCDRC and DL-LCDRC was compared with SW-LCDRC-MPSO on the reputed face database like ORL and YALE B. In this experimental examination all the facial images were cropped at the size of 32×32 and 64×64.

ORL database examination: ORL facial dataset holds 400 face images with 40 individuals, each individual contains 10 face images, respectively. The following face images were captured under numerous facial expressions and altered lightening conditions. Sample face images of ORL database is given in Fig. 1.

The effectiveness of recognition rate was verified in four different training percentages like 2 train (20% training), 4 train (40% training), 6 train (60% training) and 8 train (80% training). In Fig. 2-5, the high dimensional recognition rate was almost achieved 100% outcome in existing methods for ORL dataset. So, this research mainly concentrates on lower dimensional recognition rate. While comparing with existing approaches like LCDRC and DL-LCDRC, the proposed approach shows significant outcome in terms of accuracy.

YALE B database examination: YALE B face database holds 15 individuals with 165 face images, each individuals holds 11 facial images under altered configurations and with different facial expressions. Sample face images of YALE B dataset is mentioned in Fig. 6.

The performance of LCDRC, DL-LCDRC and the proposed SW-LCDRC-MPSO in YALE B database was determined and compared by referring Fig. 7-10. For example, the significant recognition rate and the corresponding feature dimensions were mentioned in four various training percentages. By analyzing all the training percentages, the proposed approach shows a significant outcome in YALE B dataset.

Table 1 and 2 indicate the performance analysis of SW-LCDRC-MPSO over LCDRC and DL-LCDRC for ORL and YALE B datasets. Table 1 determines the experimental outcome for 32×32 cropped size images and Table 2 shows the result for 64×64 cropped size images.

Fig. 1: ORL facial dataset

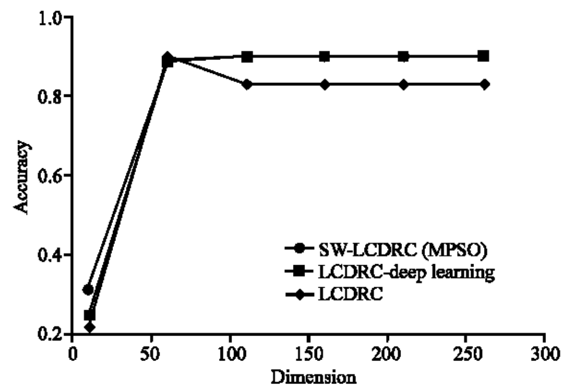

Fig. 2: Two train for ORL dataset

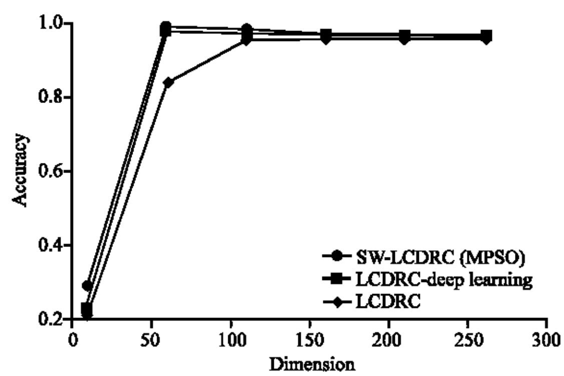

Fig. 3: Four train for ORL dataset

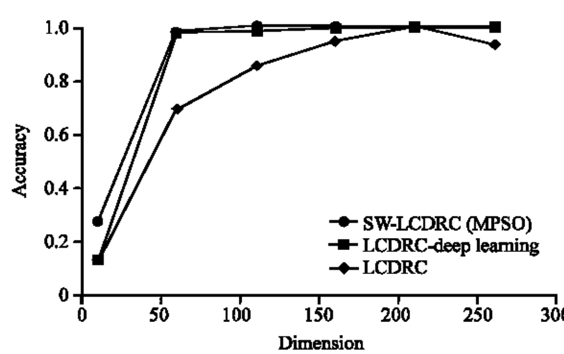

Fig. 4: Six train for ORL dataset

The experimental outcome was evaluated by adding "salt and pepper" noise in the training images. Table 3 compared the outcome values of proposed and existing methods for ORL and YALE B datasets with 32×32 cropped size images and the 64×64 cropped size images were represented in Table 4. Only, 20% training was considered in this section to attain significant result in insufficient input situations for instant, surveillance video analyzing.

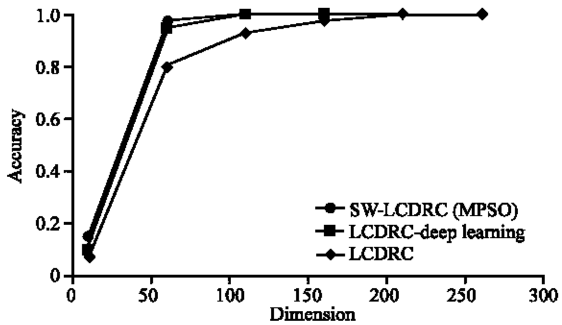

Fig. 5: Eight train for ORL dataset

Fig. 6: YALE B Face dataset

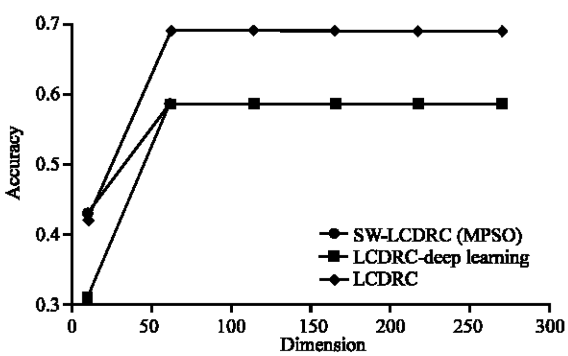

Fig. 7: Two train for YALE B dataset

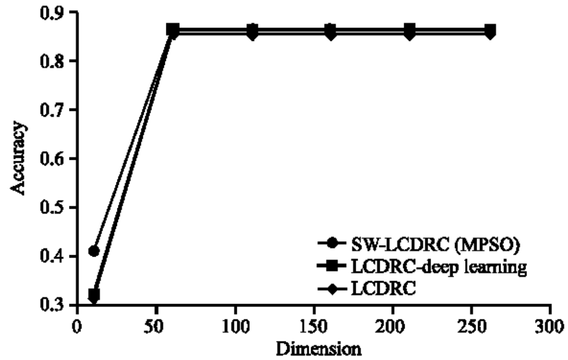

Fig. 8: Four train for YALE B dataset

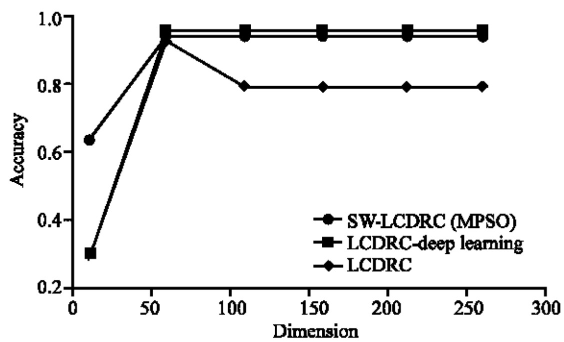

Fig. 9: Six train for YALE B dataset

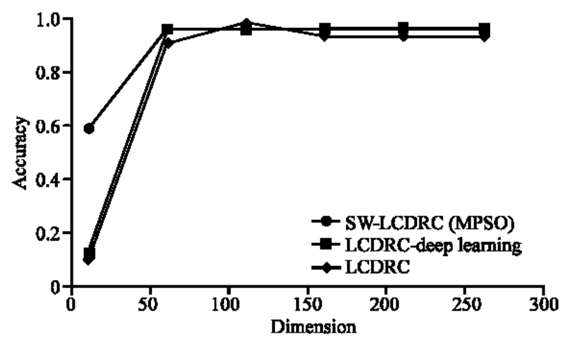

Fig. 10: Eight train for YALE B dataset

Table 1: Performance evaluation table for 32*32 image size

	Lower recognition rate (Training samples%)				Peak recognition rate (Training samples%)				Average recognition rate (Training samples%)			
Database/Methods	20	40	60	80	20	40	60	80	20	40	60	80
ORL												
LCDRC	22.1	20.8	18.7	7.5	89.6	95.4	100	100	73.8	80.9	77.6	79.5
DL-LCDRC	24.6	23.7	18.7	10	89.6	97.5	100	100	78.6	84.4	85.6	84.1
Proposed	31.5	29.1	32.5	15	90.3	98.3	100	100	80.1	85.6	88.2	85.1
YALE B												
LCDRC	42.2	31.4	28	13.3	68.8	83.8	90.6	97.7	64.4	75	71.3	73.8
DL-LCDRC	31.1	32.3	28	15.5	58.5	84.7	93.3	95.5	53.9	76	82.4	78.6
Proposed	42.9	40.9	61.3	60	58.5	84.7	92	95.5	55.9	77.4	86.8	80.1

Table 2: Performance evaluation table for 64*64 image size

	Lower recognition rate (Training samples%)				Peak recognition rate (Training samples%)				Average recognition rate (Training samples%)			
Database/Methods	20	40	60	80	20	40	60	80	20	40	60	80
ORL												
LCDRC	24	23.8	20.6	9.6	91.9	98.9	100	100	75.7	82	79	79.5
DL-LCDRC	26.6	26.2	20.5	13.4	90.8	100	98	100	80.9	86.4	86.6	84
Proposed	32.9	32.1	35.8	17.9	92.7	100	100	99.9	89.9	89.6	88.2	86.1
YALE B												
LCDRC	45.1	34.7	30.1	15.3	71.3	86.1	92.4	98.8	67.4	76.7	73	75.6
DL-LCDRC	41.4	33.6	29.7	17.7	60.5	87.2	95.1	97.2	52.5	77.8	83.8	80
Proposed	50.4	48.2	71.3	73.9	59.1	89.7	93.4	96	55.9	77.9	89.9	83.7

Table 3: Performance evaluation by adding noise for 32×32 image size

		Training samples (20%)	
Database/Methods	Noise (%)	Lower recognition rate	Average recognition rate
ORL			
LCDRC	0	22.1	73.8
	10	15.62	66
	40	5	38.1
	70	5.6	9.3
DL-LCDRC	0	24.6	78.6
	10	13.4	72
	40	6.5	39.4
	70	1.5	10.8
Proposed	0	31.5	80.1
	10	19	72.3
	40	9.6	38.3
	70	1.5	11.3
YALE B			
LCDRC	0	42.2	64.4
	10	40.7	61.1
	40	22.9	42.7
	70	11.1	22.
DL-LCDRC	0	31.1	53.9
	10	31.1	50.8
	40	17	31.2
	70	8.1	14.3
Proposed	0	42.9	55.9
	10	38.8	50.2
	40	25.1	35
	70	11.8	17.4

Table 4. Performance evaluation by adding noise for 64×64 image size

		Training samples (20%)	
Database/Methods	Noise (%)	Lower recognition rate	Average recognition rate
ORL			
LCDRC	0	22.1	73.8
	10	20.9	67.3
	40	13.4	34.6
	70	8.9	14.7
DL-LCDRC	0	24.6	78.6
	10	19	69.8
	40	14.7	54.9
	70	7.9	31
Proposed	0	31.5	80.1
	10	28.9	64
	40	17.3	54.3
	70	11.2	22.2
YALE B			
LCDRC	0	45.1	67.4
	10	47.4	66.5
	40	39.2	47.9
	70	9.6	13.9
DL-LCDRC	0	41.4	52.5
	10	42.2	52.7

Table 4: Continue

		Training samples (20%)	
Database/Methods	Noise (%)	Lower recognition rate	Average recognition rate
	40	33.3	37
	70	14	14.6
Proposed	0	50.3	55.9
	10	46.6	55.3
	40	34.8	39.7
	70	8.1	12.4

CONCLUSION

In this study, a new discriminant analysis scheme named as SW-LCDRC-MPSO is recognized for extracting the features and FR. Here, the proposed method is an improved version of LCDRC and DL-LCDRC 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 databases like ORL and YALE B that shows a superiority of the proposed methodology. The recognition rate on the sub-space is more significant in SW-LCDRC-MPSO than the previous techniques.

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