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Hybridization of Enhanced Orthogonal and Uncorrelated Locality Preserving Projection for Dimensionality Reduction: An HEOULPP Strategy

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Abstract: A recent development of a linear dimension reduction (DR) algorithm that is often used in face recognition and other applications has been used to preserve the Locality preserving projection algorithm (LPP). However, in LPP the projection matrix is not orthogonal, so rendering and other apps are not easily reconstructed. Hybridization of Enhanced Orthogonal and Uncorrelated Locality Preserving Projection (HEOULPP) attempts to discover the subspace that best distinguishes distinct face classes by maximizing the gap and reducing the uncertainty within class. In the design of a similarity matrix, HEOULPP algorithm assumes both local data and label data, and needs statistically improved and orthogonal output-base vectors, in order to enhance the OLPP life grade extraction performance. We propose HEOULPP to minimize the locality in an orthogonal projection matrix and to maximize the globality. This investigation is conducted using three datasets, such as YALE face dataset, ORL face dataset, and AR face dataset. Our proposed HEOULPP techniques achieves higher facial recognition rate under three conditions such as occlusion by 70.6%, noise by 69.1% and original by 76.2% than the existing techniques. In addition, dimensionality also reduced in proposed HEOULPP method comparing with traditional methods, including PCA, LPP, OLPP, ULPP and FOLPP. Experimental findings indicated a stronger depiction of data and much greater accuracy in the suggested HEOULPP method.

Keywords: Locality preserving projection (LPP), Dimension reduction, Hybridization of enhanced orthogonal and uncorrelated locality preserving projection (HEOULPP), Orthogonal locality preserving projection (OLPP).

1. Introduction

The dimension reduction is carried out in high-dimensional datasets before using a nearest K-algorithm (k-NN) to prevent curse of dimensionality [1] effects. Feature selection is a method for selecting a subset of initial characteristics to optimally reduce the function space by a certain assessment criterion [2]. It is essential for the removal of irrelevant and redundant characteristics, to improve the learning effectiveness and to improve the precision and the understanding of studied results [3]. High-dimensional data (i.e. hundreds or thousands of data sets) can comprise elevated levels of information that is non-relevant and redundant and could significantly degrade the efficiency of learning algorithm [4]. Thus the choice of functions is very important in the face of high-dimensional information for computer training activities [5]. This tendency to enormity on both magnitude and dimensionality also presents serious problems with algorithms of selection [6]. In the course of latest studies in feature selection [7] these problems have been concentrated [8]. This research focuses on high dimensional information feature selection. Two widely-used techniques for dimensional reduction include principle component analytical (PCA) and linear discriminant analysis (LDA) [9]. The worldwide Euclidean data structure is considered by both PCA and LDA but they have little to gain from the varied data structure. In view of that, it has been proposed to examine the sub-manifold structure of the data using new methods of extraction of functions, for example, Locally Linear Incorporation (LLI) [10], Isomap [11], Local Projection

Preservation [12], Chart Embedding [13] and their extensions [14, 15]. All these techniques are tried to embody the initial information in a sub-manifold. The determination of explicit mapping is very difficult while using some dimension reduction techniques, such as PCA [16], LDA [17], locally linear embedding (LLE) [18], etc. To solve the explicit mapping difficulty, some researches introduce LPP [19] method to preserve the local structure of data, which is mainly for dimension reduction and feature extraction. Moreover, LPP matrix is not orthogonal, and it creates some problem while reconstructing the data. For that, orthogonal LPP (OLPP) [20] was employed to eliminate the non-orthogonal problem, and it affected due to high computational complexity and cost. Various researchers give attention to alleviate the complexity evolved in OLPP, the new approach Fast and orthogonal LPP (FOLPP) is carried out to reduce the complexity and expensive problem, this FOLPP [21] minimizes the locality and maximizes the globality simultaneously under orthogonality. Recognition rate of FOLPP less when comparing to our proposed HEOULPP method. The above mentioned problems are eliminated by adopting our proposed HEOULPP technique. The main contributions of our proposed work are as follows,

- We propose a hybridization of enhanced orthogonal and uncorrelated locality preserving projection (HEOULPP) for dimensionality reduction.
- Orthogonal constraints are necessary to preserve the metrical structure of the data, while uncorrelated restrictions have the minimum redundancy for the extracted features.
- The HEOULPP method suggested minimizes locality and concurrently maximizes worldwide under the orthogonal threshold.

Rest of the paper is organized as follows, Section 2 illustrates the existing works related to Locality preserving projections. Section 3 describes various works pertaining to the use of Locality preserving projections. Section 4 describes the proposed methodology on Orthogonal Locality preserving projections (OLPP). Section 5 describes the proposed methodology on Uncorrelated Locality preserving projections (ULPP). Section 6 describes the proposed methodology on Hybridization of Enhanced Orthogonal and Uncorrelated Locality Preserving Projection for Dimensionality Reduction (HEOULPP). Section 7 presents the experimental results. Section 8 defines the conclusion.

2. Preliminaries

2.1 Locality preserving projections

LPP is a well-known Laplacian Eigen map linear subspace teaching algorithm. In order to find the corresponding s_k=R^m in the small dimensional manifold for t_k, the Laplacian Eigen map is used to solve the following optimization problem with each training data point,

$$V = t_1, t_2, \ldots t_n \in R^{d\times n} \tag{1}$$

where t_1, t_2,…, t_n represents training data point. To resolve each training data point t_k= R^m, Laplacian Eigen map is used:

$$\min_{TDM^F=K} \sum_{k,l=1}^{n} B_{kl} \|s_k - s_l\|^2 = \min_{TDM^F=K} fp(TLMT^F) \tag{2}$$

where $$T = [s_1, s_2, \ldots \in R^{m\times n}] \tag{3}$$

The term $fp(TLMP^F)$denotes the trace operator and K is an identity matrix. And B_{kl} measures the similarity of t_k and t_l.. DM is a diagonal matrix with elements is represented in Eq. (4). $LM = DM - B$ is a Laplacian matrix defined on a graph constructed by the training data points. The similarity matrix B is defined frequently as in Eq. (5)

$$DM_{kk} = \sum_{l=1}^{n} B_{kl} \tag{4}$$

$$B_{kl} = \begin{cases} e^{-\|t_k - t_l\|^{2}/y} & t_k and t_l areneighbours \\ 0 & otherwise \end{cases} \tag{5}$$

where y is the heat kernel parameter and ||.|| denotes the l2-norm. In Eq. (5), the similarity B_{kl} increases gradually with reduction of distance between t_k and t_l. Thus, If neighboring points t_k and t_l are mapped far apart then B_k incurs huge reprimand. The net impact of reducing the target function is to preserve the locality, i.e. if t_k and t_l are near, s_k and s_l are also near. Smaller similarities between t_k and t_l should also contribute to wider gaps between s_k and s_l in order to minimize them. The map from t =R^m to s = R^m of the Laplacian Eigen map is not linear. The Eigenmap can only recognized information points while LPP can map the information points with a linear projection matrix easily. The map t = R^m to S = R^m be linear, according to LPP, let

$$S = G^F V \tag{6}$$

$$G = g_1, g_2, \ldots g_m \in R^{d\times m} \tag{7}$$

where G is a projection matrix. In order to overcome another optimizing problem LPP can be used, by enforcing a linear connection of Eq. (6) on optimizing problem of Eq. (2).

$$\min_{G^F VDMV^F G=K} p(G^F VLMV^F G) \quad (8)$$

From the Eq. (8) the LPP algorithm takes the overall data and does not minimize projection locations. The projection matrix G, is not orthogonal and causes rebuilding of other apps difficult. Finally, to fix the previous issue of self-decomposition, the solution of this optimization problem will be reduced:

$$VLMV^F G = VDMV^F G\Lambda \quad (9)$$

where Λ is the eigenvalue matrix and G is the corresponding eigenvector matrix of $(VDMV^F)^{-1}VLMV^F$. The total computational complexity of LPP is $2a^3 + 2a^2n + a^2m + an^2$.

3. Literature review

Various research works have already existed in the literature, which depend on dimensionality reduction with different perspectives. A portion of the works is reviewed on here.

An improved version of social spider optimization algorithm called SSORS algorithm [22] has been used to make the feature selection feasible. It could remove the insignificant characteristics without reducing rating performance. The drawback was that very high-dimensional datasets could be identified difficult. In 2018, Zhu et al. [23] developed a class weights random forest (CWsRF) to process the class imbalanced medical data, by assigning separate weights for every class rather than single weights. Threshold votes were used to classify the improved votes. The main drawback is the slow convergence. In 2018, Liu et al [24] presented a Quasi-curvature Local Linear Projection (QLLP) to reduce the dimensionality efficacy. Extreme learning machine was used for mapping function from original data to low dimensional coordinates for nonlinear dimension reduction but the complexity is high. In 2018, Divya Jain and Vijendra Singh [25] proposed a hybrid feature selection approaches based on the fusion of ReliefF and PCA method to reduce the dimensionality of features. The space limitation is the main disadvantage. In 2018, Deng et al. [26] have introduced a modified tensor locality preserving projection (MTLPP) algorithm to lessen the dimensionality and noise of hyperspectral image (HIS). Log-Euclidean metric were deployed as a similarity measure to determine the nearest neighbor. The support vector machine (SVM) technique for selecting functionality provided for the tiny amount of features chosen and guarantees a strong identification rate by Qiong Liu, QiongGu et.al [27]. But the computational complexity is high in this model. In 2018, Yu et al. [28] have introduced improved locality preserving projection with ℓ_1-norm minimization (ILPP-L1) to enhance the robustness and effectively preserve the similarity of pair of vertices. The computational time is high for the minimization process. Joint sparse representation and locality preserving projection (JSRLPP) [29] was developed to extract the feature in the combined manner, and it learns the similarity and projection matrix concurrently. But the interpretability is not good.

4. Orthogonal locality preserving projection (OLPP)

The orthogonal technique was highlighted, because orthogonality with excellent empirical efficiency is desirable. It is suggested to search for an adaptive mapping matrix W which links the high dimensional information point $t \in R^d$ to the low dimension information point $s \in R^m$ orthogonal LPP (OLPP) method is used [20] to minimize weighted data variance of local data pair ranges. It is necessary to minimize locality and maximize globality simultaneously to obtain more discriminatory authority which is formulated as:

$$fp\left(G^{\mathrm{F}} H K_a H^F G\right) = a \sum_{K=1}^{\mathrm{n}} s_k ||Z_k - \bar{Z}\,||^2 \quad (10)$$

where $fp(G^F HK_a H^F G)$ is the weighted data variance that can be viewed as worldwide information in data. It is inevitably consequent to minimize $fp(G^F HKH^F G)$ and maximize $fp(G^F HK_a H^F G)$ at the same time. In this regard, the following two criteria can reasonably be selected as:

$$Q_1(\mathrm{G}) = fp(G^F H(\lambda k - K_a) H^F G \quad (11)$$

$$Q_2(G) = \frac{fp(G^F HKH^F G)}{fp(G^F HK_a H^F G)} \quad (12)$$

where λa standard that is user-defined. The two requirements above both meet the shift-invariance property are convenient to see. We attach a limitation as $G^F HG = 1$ to achieve an orthogonal projection matrix G then address the following two optimization issues:

$$G = \arg \min_{G^T G=1} fp(G^F H(\lambda K - K_a)H^F G) \quad (13)$$

$$G = \arg \min_{G^T G=1} \frac{fp(G^F HKH^F G)}{fp(G^F HK_a H^F G)} \quad (14)$$

The decomposition of the individual $H(\lambda K\text{-}K_a)H^F$ as follows can readily be achieved based on solution to Eq. (14).

$$\mathrm{H}(\lambda k - K_a)H^{\mathrm{F}}G = G\Lambda \quad (15)$$

where Λ is the eigenvalue matrix of $H(\lambda K\text{-}K_a)H^F$ and G is the corresponding eigenvector matrix. Using Eq. (15) is a bit uncompromising. The overall graphic-based feature extraction structure can provide a solution to optimization problems of Eqs. (14) and (15). The various Laplacian matrices K and K_a are designed in separate uncontrolled, semi-controlled or supervised circuits for feature removal. Objective function could minimize on the basis of obtained k-th basis vector.

$$Q_2(G_k) = \frac{fp_k({G_k}^F HKH^F G_k)}{fp_k({G_k}^F HK_a H^F G_k)} \quad (16)$$

With the constraints${G_k}^F G_1 = G_k G_2 = \ldots {G_k}^F G_{k-1}=0$, ${G_k}^F HKH^F G_k$. Lagrange multipliers are used to change the above objective function to incorporate all the constraints.

$$s^{(k)} = {G_k}^F HKH^F G_k - \delta({G_k}^F HK_a H^F G_k - 1) - \varepsilon {G_k}^F G_1 - \cdots - \epsilon_{k-1} {G_k}^F {G_{k-1}}^F. \quad (17)$$

where G is the Eigen vector of the matrix.

5. Uncorrelated locality preserving projection (ULPP)

In the case of uncorrelated LPP (ULPP), our aim is to maintain the local structure of the data set and at the same time retain the information between locations in the data set. ULPP [30] seeks to discover, in general, an optimum conversion that retains the information set's inherent geometry. Let $t_1, t_2, \ldots t_n$ be the low-dimensional space that is projected. This proposes the objective function of ULPP:

$$\mathrm{P}(X) = \sum_{k,l=1}^{m} (\mathrm{w}_k - w_l)^2 - \sum_{k,l=1}^{n} (s_k - s_l)^2 G_{kl} = P_d(\mathrm{X}) - P_E(\mathrm{X}) \quad (16)$$

If X is a transformation vector then the conversion is $s = X^F t$. The minute of objective function can be decreased with simple algebraic analysis:

$$\begin{aligned} P_d(X) &= \sum_{k,l=1}^{m} (w_k - w_l)^2 \\ &= \sum_{k,l=1}^{m} (\sum_{t \in u_k} \frac{1}{n_k} X^F t - \sum_{t \in u_1} \frac{1}{n_1} X^F t)^2 \\ &= \sum_{k,l=1}^{m} X^F (\bar{t}_{uk} - \bar{t}_{ul})^F \mathrm{X} \\ &= 2\mathrm{X}^{\mathrm{F}} H_{\mathrm{d}} \mathrm{X} = 2\mathrm{X}^{\mathrm{F}} \mathrm{VDV}^{\mathrm{F}} X \end{aligned} \quad (17)$$

where

$$w_k = \left({}^{1}/_{nk}\right) \sum_{s \in u_k} s, \bar{t}_{uk} = \left({}^{1}/_{uk}\right) \sum_{t \in u_k} t \quad (18)$$

The subtrahend of objective function can be reduced to

$$\begin{aligned} P_E(X) &= \sum_{k,l=1}^{n} (s_k - s_l)^2 G_{kl} \\ &= \mathrm{X}^F \left(\sum_{k,l=1}^{n} (t_{uk} - t_{ul})(t_{uk} - t_u)^F \right) \mathrm{G}_{kl}) X \\ &= 2X^F VEV^F X \end{aligned} \quad (19)$$

Substituting $P_L(X)$ and $P_d(X)$ into the objective function (19), wehave

$$P(X) = 2X^F V(D - E)V^F X \quad (20)$$

Next, the constraint is considered and we also impose a constraint $X^F VQV^F X=1$.The corresponding restricted maximization issue is developed as ULPP:

$$\max \mathrm{P(X)} = \max_{x^F VQV^F X=1} 2X^F V(D - E)V^F X \quad (21)$$

Maximum value alternatives for the general self-values issue are provided for the vectors $\{x_k\}$ which achieve the objective feature:

$$\mathrm{V}(D - E)V^F x = \lambda \mathrm{VQ} V^F x \quad (22)$$

The statistics $V(D - E)V^F$ andVQV^Fcan easily isshown. The vectors $x_k (K=0,1,2,\ldots.e\text{-}1)$ that maximize the target feature are provided to a generalized value issue using highest eigenvalue solutions. The linear characteristics will be obtained by$s = X^F t$ when X is acquired.

6. Hybridization of enhanced orthogonal and uncorrelated locality preserving projection for dimensionality reduction (HEOULPP)

Orthogonal and Uncorrelated locality preservation of a projection algorithm oscillates the ULPP routinely. The following is described as:

1) Evaluation of PCA performed. We are projecting the data into a PCA subspace to make the VQV^Fmatrix un-individual. Let the transformation matrix of PCA be oscillating with Φ_{PCA}.
2) Develop the likeness between two points of information. Set the *ratio*$g_{kl}=g_{lk}=t_k^F t_l$, otherwise the *range*$g_{kl}=g_{lk}=0$ for each sample t_k is between the m-nearest neighbors to t_k the similitude reflects the local data space composition.
3) Obtain the diagonal matrix *DM* and the Laplacian matrix *LM*.
4) Compute the Orthogonal and Uncorrelated locality preserving projections. Let $A_{LM}=VLMV^F$, $A_{DM}=VDMV^F$ and $K=diag(1,1,\ldots 1)$ for concision. Let $\{\phi_1, \phi_2, \ldots \ldots \phi_m\}$ be the Orthogonal and Uncorrelated locality preserving projections, hence we define,$\Phi(m\text{-}1)= \{\phi_1,\phi_2,\ldots.,\phi_{n-1}\}$

The Orthogonal and Uncorrelated locality preserving projections$\{\phi_1,\phi_{2,\ldots,}\phi_m\}$can be iteratively computed as follows:

a) Compute ϕ_1 as the eigenvector of $A^{-1}{}_{DM}ALM$ associated with the smallest eigenvalue.
b) Compute ϕ_m as the eigenvector associated with the smallest eigenvalue of the Eigenfunction.

$$B^{(m)} A_{LM} \phi = \lambda A_{DM^{\phi}} \tag{23}$$

where $B^{(m)} = k - \Xi(\Phi^{(m-1)})^F (\Phi^{(m-1)} \Xi A_{DM}^{-1} \Xi(\Phi^{(m-1)})^F)^{-1} \times \Phi^{(m-1)} \Xi A_{DM}^{-1}$ (24)

5) Perform the HEOULPP transformation. Let $\Phi^{*}=\{\phi_1,\phi_2,\ldots\ldots\phi_e\}$. The embedding is as follows:

$$\mathrm{q} = \Phi^F_{\mathrm{HEOULPP}^{\mathrm{r}}} \tag{25}$$

where q is a d-dimensional representation and $\Phi_{HEOULPP}=\Phi_{PCA}\Phi^{*}$.

7. Experimental results

7.1 Face recognition using YALE face data set

In this aspect the achievement with distinct facial expressions or configuration of HEOULPP is evaluated. As shown in Fig.1, Yale face database pictures contain 165 GIF-scale pictures for 15 people. There are 10 pictures per topic, one per facial exposition or setup: center-light, glass, happy, left-light, glass-free, ordinary, right-light, sad, sleepy, amazed, and wink. We selected 4 pictures of each individual (center light, left light, normal and happy), and the rest of the database was the test collection. Therefore, the sample size for training is 60 and the sample size for tests is 105. Each picture is trimmed and re-dimensioned deliberately to 32 pixels per 32 pixels.

Fig. 1 shows the sample pictures of a participant from the Yale face dataset. The picture samples are divided simultaneously so that l (l= 2, 3, 4, 5, 6) pictures are collected and marked for each individual person to create a training set, while others are used as a test set.

In this test, the database is randomly divided into 60% training and 40% test specimens to check the efficiency of the suggested algorithm. The identification frequency outcomes for YALE face dataset are shown in the Fig. 2. The HEOULPP identification in YALE is greater than in PCA, LPP, ULPP, OLPP and FOLPP because it utilizes the class data of samples and improves the identification frequency quickly, overcoming other algorithms with the rise of the amount of characteristics. The

Figure.1 Samples from YALE face database

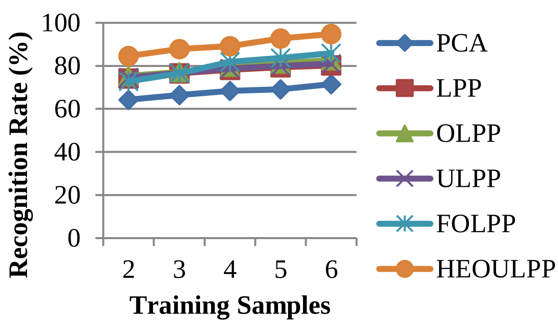

Figure.2 Face recognition rates (%) vs. training samples in the YALE face dataset.

Table 1. Face recognition error rates (%) of methods for YALE face database

Algorithm	Number of Training Samples				
	2	3	4	5	6
PCA	55.78	50.67	47.08	43.33	41.04
LPP	42.42	31.09	25.58	20.64	8.52
OLPP	41.74	27.33	21.46	15.72	14.23
ULPP	41.23	27.12	22.78	15.01	14.02
FOLPP	40.98	26.03	22.43	14.64	13.08
HEOULPP	39.63	25.12	21.82	13.21	12.09

best outcomes and ideal dimensionality of error rate of the PCA [9], LPP [19], ULPP [20], OLPP [30], FOLPP [21] and HEOLPP algorithms can be summarized in Table 1. Our HEOULPP algorithm delivers the maximum output, which can be seen in the results. For 2 training samples, the recognition error rate of the proposed method is 39.63%, for 3 training samples the error rate is 25.12%, for 4 samples the recognition error rate is 21.82%, for 5 training samples the error rate is 13.21% and for 6 training samples the recognition error rate of HEOULPP is 12.09% for YALE face database.

Fig. 3 shows the recognition error rate plots versus the decrease in dimensionality for different sets of training samples. Our HEOULPP algorithm was relatively better with LPP and OLPP, while the PCA algorithm did not succeed excellently. Table 2 describes the training samples of the recognition rate of PCA, LPP, ULPP, OLPP, FOLPP and HEOLPP algorithms.

The observed CPU time of training in PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms is shown in Table 3 in YALE face data sharing. Fig. 4 describes the training time versus the dimensions of PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms. The HEOULPP performs best comparatively in utilizing the CPU time.

7.2 Face recognition using ORL face data set

A total of 400 images, of which 40 persons, 10 samples per person are shown in the Fig 5, are part of the ORL face database. Face image is cropped and resized to 64x64, the size of which shifts, with or without lenses, including tiny modifications in facial expressions and movements, within 20%.

In each test performed, Table 4 summarizes the finest outcomes and the optimum dimension for each algorithm. The HEOULPP algorithm seemed to be most successful. For 2 training samples, the recognition error rate of the proposed method is 25.05%, for 3 training samples the error rate is 24.93%, for 4 samples the recognition error rate is 23.09%, for 5 training samples the error rate is

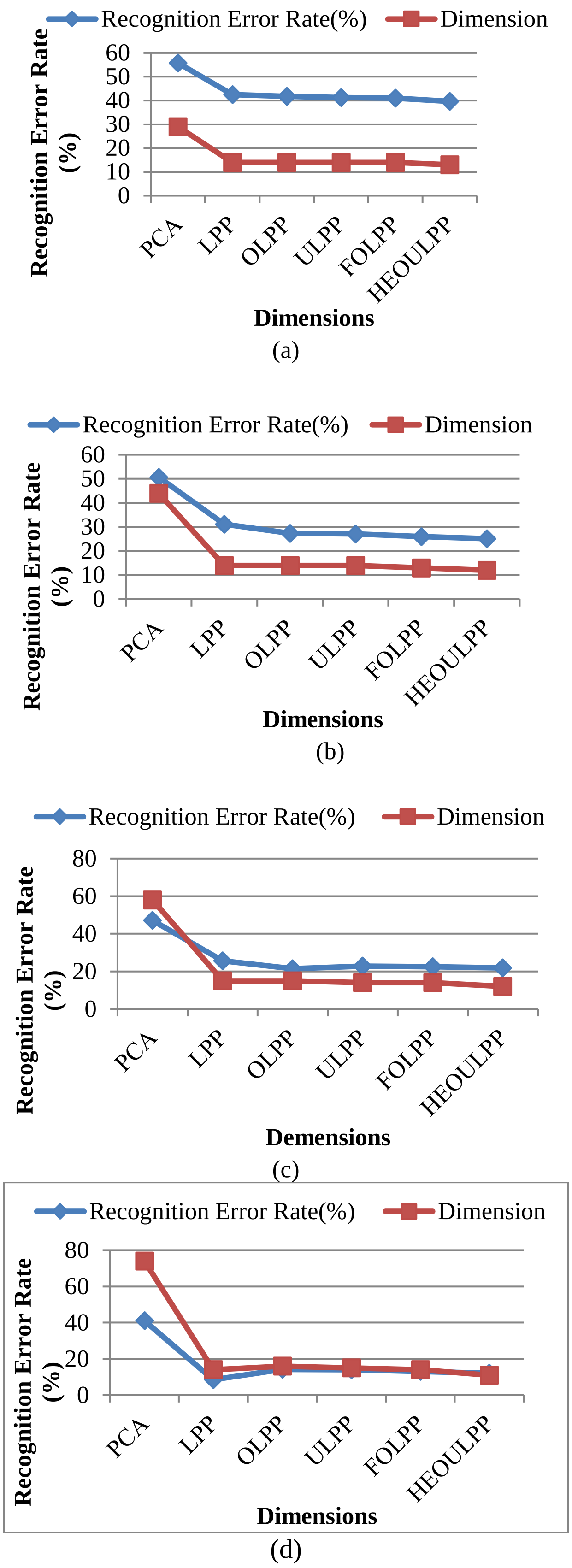

Figure.3 Face recognition error rates (%) vs. dimension in the YALE face dataset: (a) training Set- 2, (b) training set- 3, (c) training set- 4, and (d)training set- 6

Table 2. Face recognition rates (%) of methods for YALE face database

Algorithm	Number of Training Samples				
	2	3	4	5	6
PCA	64.3	66.5	68.4	69.2	71.5
LPP	74.2	76.5	78.2	79.3	80.2
ULPP	75.4	77.1	79.7	81.2	82.7
OLPP	74.6	76.7	78.8	79.9	81.0
FOLPP	72.8	76.5	81.9	83.6	85.9
HEOULPP	84.6	87.9	89.2	92.7	94.8

Table 3. Training time in seconds for the methods on YALE face database

Algorithm	Number of Dimensions				
	100	200	300	400	500
PCA	8.4s	34.8s	63.4s	143.4s	520.1s
LPP	9.1s	47.1s	85.7s	231.8s	982.1s
ULPP	12.4s	53.5s	98.5s	481.6s	1110.4s
OLPP	30.6s	97.4s	671.3s	982.4s	2413.5s
FOLPP	62.4s	181.4s	852.6s	2810.7s	4181.2s
HEOULPP	44.5s	59.6s	124.1s	320.3s	524.8s

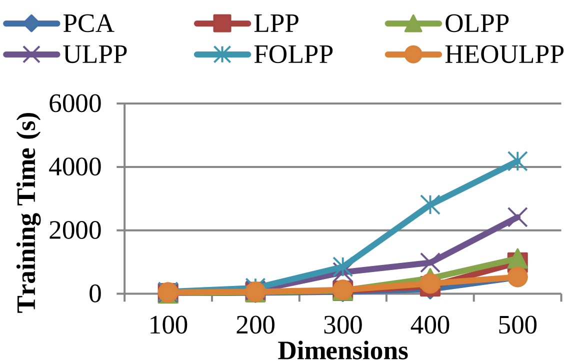

Figure.4Training time in seconds vs. dimensions


Figure.5Samples from ORL face database

Table 4. Face recognition error rates (%) of methods for ORL face database

Algorithm	Number of Training Samples				
	2	3	4	5	6
PCA	33.14	30.92	28.73	26.58	24.13
LPP	31.52	29.12	27.48	25.62	23.46
ULPP	30.61	28.34	26.62	24.43	22.38
OLPP	29.33	28.42	26.74	24.46	23.12
FOLPP	27.55	26.68	25.79	23.65	22.03
HEOULPP	25.05	24.93	23.09	22.68	21.43

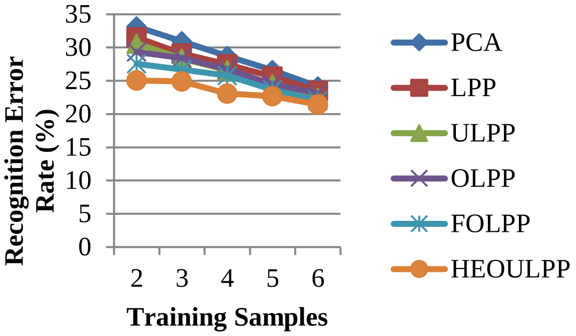

Figure.6 Face recognition error rates (%) vs. training samples in the ORL face dataset

Table 5. Face recognition rates (%) of methods for ORL face database

Algorithm	Number of Training Samples				
	2	3	4	5	6
PCA	63.7	64.2	65.7	66.9	67.8
LPP	73.4	75.2	76.5	78.7	79.6
OLPP	73.8	75.9	78.1	79.6	81.8
ULPP	73.6	75.3	77.9	79.3	80.6
FOLPP	71.5	74.6	80.7	82.6	84.2
HEOULPP	83.5	85.6	87.3	89.5	91.7

22.68% and for 6 training samples the recognition error rate of HEOULPP is 21.43%. Fig. 6 shows the recognition error rate plots versus the decrease in dimensionality. In HEOULPP algorithm the error rate performs efficiently comparing to other algorithms.

For ORL, the training sets included 5 random sub-sets of (l= 2, 3, 4, 5, 6) pictures per person. First of all, compare the finest PCA, LPP, ULPP, OLPP, FOLPP identification accuracies and our suggested HEOULPP on ORL Face database. The finest recognition of the six techniques with sub-sets (l= 2, 3, 4, 5, 6) are summarized in Table 5.

The averaged outcomes for every given l over 20 random divided divisions. For 2 training samples, the recognition error rate of the proposed method is 83.5%, for 3 training samples the error rate is 85.6%, for 4 samples the recognition error rate is 87.3%, for 5 training samples the error rate is 89.5% and for 6 training samples the recognition error rate of HEOULPP is 91.7% for ORL database.This can be seen, in most training activities the HEOULPP serves excellent. The identification frequency outcomes for ORL Face dataset are shown in the Fig. 7. By comparing HEOULPP with PCA, LPP, ULPP, OLPP, FOLPP, the HEOULPP performs significantly. The observed CPU time of training in PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms is shown in Table 6 in ORL data sharing. Fig. 8 describes the training time versus the

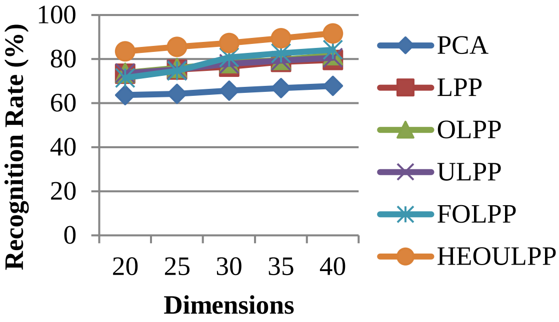

Figure.7 Face recognition rates (%) vs. dimension in the ORL face dataset

Table 6. Training time in seconds for the methods on ORL face database

Algorithm	Number of Dimensions				
	100	200	300	400	500
PCA	21.7s	42.2s	84.1s	96.3s	110.2s
LPP	31.8s	68.4s	89.3s	109.4s	560.3s
ULPP	43.9s	150.7s	620.6s	973.2s	2467.1s
OLPP	58.3s	2281.8s	962.4s	2371.1s	5843.2s
FOLPP	79.5s	2564.5s	4014.9s	4213.8s	6014.7s
HEOULPP	63.4s	896.3s	1853.5s	4160.4s	5095.5s

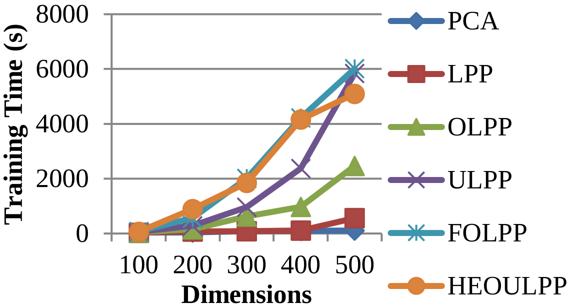

Figure.8 Training time vs. dimensions

Figure.9 Samples from AR face database

dimensions of PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms. The HEOULPP performs best comparatively in utilizing the CPU time.

7.3 Face recognition using AR face data set

AR face Database comprises of more than 4000 pictures of 126 color face pictures (70 males and 56 females). In two sessions (separated by two weeks), the image of the most individuals (65 men and 55 women) is taken. The pictures from each event consist of three illuminated pictures, three wearing scarf pictures, three sun glass pictures and four expressive variants. Table 7 records highest median recognition rates with distinct samples of training, and associated standard deviations of the various techniques. In contrast to PCA, LPP, ULPP, OLPP and FOLPP, the suggested technique (HEOULPP) has achieved the highest acceptance frequency. Fig. 10 shows the detection frequency vs. dimensionality, where we selected five samples of practice per individual.

Table 7. Face Recognition rates (%) of methods for AR face database

Algorithm	Number of Training Samples				
	2	3	4	5	6
PCA	62.5	64.8	66.8	67.4	69.5
LPP	71.7	74.2	77.2	78.2	81.4
ULPP	72.6	75.2	78.3	80.2	82.7
OLPP	72.2	74.8	77.7	79.0	81.9
FOLPP	74.5	76.1	80.8	83.9	87.3
HEOULPP	80.1	87.4	90.4	93.8	96.9

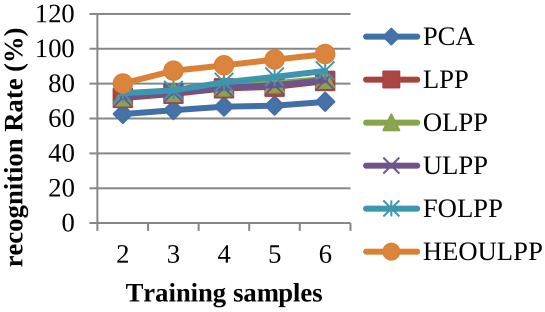

Figure.10 Face recognition rates (%) vs. training samples in the AR face dataset

Table 8. Training Time in Seconds for the methods on AR face database

Algorithm	Number of Dimensions				
	100	200	300	400	500
PCA	10.4s	37.3s	48.7s	73.4s	98.1s
LPP	12.8s	35.8s	59.4s	111.7s	179.8s
ULPP	35.2s	143.4s	527.6s	981.6s	3210.7s
OLPP	34.6s	267.1s	838.4s	2757.5s	7764.4s
FOLPP	64.3s	502.4s	1582.3s	4690.5s	9949.3s
HEOULPP	46.7s	99.4s	181.5s	346.4s	601.4s

The observed CPU time of training in PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms is shown in Table 8 in AR data sharing. Fig. 11 describes the training time in seconds versus the dimensions of PCA, LPP, ULPP, OLPP, FOLPP and HEOULPP algorithms. The HEOULPP performs best comparatively in utilizing the CPU time. Table

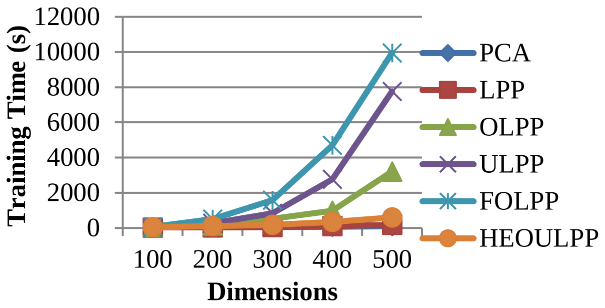

Figure.11Training time vs. dimensions

Table 9. Face recognition rates (%) of methods under different conditions

Algorithm	Recognition Rate (%)		
	Occlusion	Noise	Original
PCA	51.6	50.2	64.6
LPP	58.9	56.1	71.3
OLPP	67.8	63.2	73.6
ULPP	69.1	66.6	74.0
FOLPP	69.9	67.8	74.8
HEOULPP	70.6	69.1	76.2

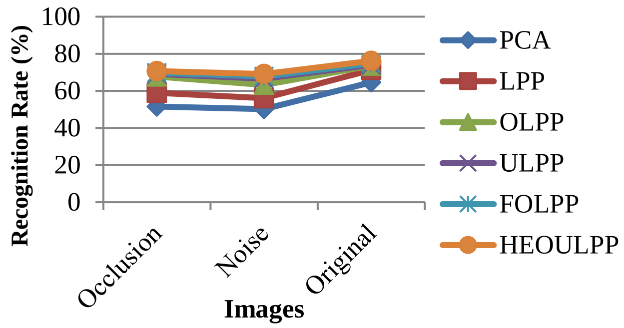

Figure.12 Recognition rates (%) vs. different images

9 shows the recognition rates of the techniques under different conditions, which says, occlusion has less influence on the recognition rate of HEOULPP. Fig. 12 represents the recognition error under different conditions.

8. Conclusion

In this paper, the Hybridization of enhanced orthogonal and uncorrelated locality preserving projections (HEOULPP) is suggested. In HEOULPP technique, we first use the PCA to decrease the spaces. In designing the similarity weight matrix, HEOULPP takes account both of local information's and class labels and requires that the output base vectors be orthogonal and statistically uncorrelated which performs a crucial role in the automation of high-dimensional moment-frequency domain functionality sets. This investigation is conducted using three datasets, such as YALE face dataset, ORL face dataset, and AR face dataset. Our proposed HEOULPP techniques achieves higher facial recognition rate under three conditions such as occlusion by 70.6%, noise by 69.1% and original by 76.2% than the existing techniques. In addition, dimensionality also reduced in proposed HEOULPP method comparing with traditional methods, including PCA, LPP, OLPP, ULPP and FOLPP. These findings showed that the location was minimized and the globality effectively maximized under orthogonal projection matrices at the same time. Our future work is to extend HEOULPP for facial image recognition deployed to nonlinear form by kernel trick.

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