Single Image Face Recognition Using Laplacian of Gaussian and Discrete Cosine Transforms

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Abstract: *This paper presents a single image face recognition approach called Laplacian of Gaussian (LOG) and Discrete Cosine Transform (DCT). The proposed concept highlights a major concerned area of face recognition i.e., single image per person problem where the availability of images is limited to one at training side. To address the problem, the paper makes use of filtration and transforms property of LOG and DCT to recognize faces. As opposed to conventional methods, the proposed idea works at pre-processing stage by filtering images up to four levels and then using the filtered image as an input to DCT for feature extraction using mid frequency values of image. Then, covariance matrix is computed from mean of DCT and Principal component analysis is performed. Finally, distinct feature vector of each image is computed using top Eigenvectors in conjunction with two LOG and DCT images. The experimental comparison for LOG (DCT) was conducted on different standard data sets like ORL, Yale, PIE and MSRA which shows that the proposed technique provides better recognition accuracy than the previous conventional methods of single image per person i.e., $(PC)^2A$ and PCA, 2DPCA, B-2DPCA etc. Hence with over 97% recognition accuracy, the paper contributes a new enriched feature extraction method at pre-processing stage to address the facial system limitations.*

Keywords: *Single image, face, recognition, DCT, LOG, mid frequency values.*

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1. Introduction

The challenge that has surrounded the people round the globe is security and face recognition is among one of the methods that could provide and enhance the security. The face recognition can provide high amount of accuracy with low intrusiveness by deploying face recognition methods. The potential area of applying Face Recognition Technology (FRT) is law enforcement agencies, airports, intelligence offices and even hotels. So, to fulfil the demand of this application area, the FRT has achieved a comprehensive requirement over the past decades. Authors and researchers have evaluated the field of face recognition from different aspects and to different scenarios of their deployment. The face recognition can be further divided into different datasets to match the images from the input. The most efficient and old method to recognize face is the standard Eigenface [10] technique called Principal Component Analysis (PCA) [13]. However, the researchers have ignored a major aspect of face recognition i.e., single image per person problem which needs to be addressed more efficiently and effectively over the years. Because of ignoring such an important problem, certain well know methods i.e., Eigenface [10, 31], Fisherface [29] and elastic bunch graph matching [25] show very low recognition accuracy or even fail.

1.1. History of Problem

The history of the problem to be elaborated is that we were provided with a dataset of one image against every person. The previous techniques use that image to recognize the individual's input image from the large scale dataset under different pose and illumination conditions. In the past few years, some researchers have worked in this sub-area of face recognition and developed certain methods to address this problem such as synthesizing actual images [15], probabilistic matching [14] and neural network method [24], Fisherfaces [4, 16, 29].

The basis of one test trouble was tracked back from the earlier time of basic face recognition methods [31] where the researchers have utilized various configurable features using the space linking the two eyes. The space was then stored as a template and later used for recognition purpose. At the same time, the appearance based technique was introduced that calculates and computes faces on the basis of vectors and provides better recognition accuracy by utilizing less laborious effort.

1.2. Challenges to Problem

The challenge to the area was fortunately the learning mechanism which was considered by researchers and it has really affected the results on the availability of few face samples. Unfortunately, considering the real world application, especially in the area of law enforcement agencies and driving license, there is availability of one image per person. It is a fact that collecting samples is costly in some cases and sometimes we cannot even do so.

This paper defines a pre-processing technique which is a venture of Laplacian of Gaussian (LOG) and Discrete Cosine Transform (DCT). The new technique has been introduced with focus to address the single image per person problem by enhancing the input image with the levels of LOG filter to get better recognition percentage than the conventional input image of projection based PCA [13].

2. Related Work

As paper is highlighting face recognition with major focus on single image per person problem, there are some methods that provide us with results on single image problem over the past decade [9, 11, 21, 23, 26, 32]. The difference among techniques lies in how they compute features of the face for recognition purpose and the way they notify that input image has been matched with the one stored in dataset. Examples of such techniques are Linear Discriminative Analysis (LDA) based subspace algorithm [9], Support Vector Machine (SVM) [29] etc.

In PCA, the face images are anticipated onto characteristic space that encodes the distinction among the acknowledged face images. In this way, the face is transformed into a set of characteristics called Eigenfaces. The advantage of this technique is the dimensionality reduction. This reduction removes the useless information in the face and decomposes it into orthonormal components. The face can then be represented as the weighted sum [13]. After that, the test image is compared against a training image by computing the distance between their feature vectors. It requires the frontal face image to work efficiently otherwise the result will be poor performance. 2DPCA is in fact based on 2D matrix as compared to PCA which was based on the sense of 1D vector [28]. This paper defines the 2D PCA as a row based PCA. The technique directly computes the Eigenvectors of covariance matrix without matrix to vector conversion. The idea behind this mode of recognition is to find out the most favourable projection vectors in the row track irrespective of image to vector revolution. This proves that it estimates the covariance matrix from the row of images and then computes its Eigenvector as feature vector, with the size of the covariance matrix identical to the length of image [33]. It explains the fact of face recognition with focus on the single image per person which was lacked by PCA. PBPCA [26] computes the projection along the X and Y axis of the image to help in keeping only the information of important features. It involves a threshold value for the extraction of important features. This functionality is performed at the pre-processing stage of face recognition. The average intensity of input image will be equal to the projection map image with useful information only. Hence it is better than PCA. Therefore PB PCA [26] projects better images than PCA [13].

LDA is a method from the subspace algorithms which provides a goal to find the most discriminative projection direction in Eigenspace [23]. It works on the principle of maximizing the ratio of inter as well as intra-person variation, but this subspace method has left us again with undiscovered area of single image. It is because LDA provides worst results than the conventional PCA [13]. Also, this method was not able to obtain intra-person variation required to meet the aspects of single image problem. Probabilistic based face recognition method [15] introduces face recognition using the probability of image and difference of test image prototype estimation classes to achieve better intra-person variation. Such techniques were also left behind with same result on the issue of single image.

The face recognition techniques have now been evolved around the filtering of image to get better results and for that they have used the evaluation pursuit [26] and Laplacian faces [4, 5, 26] to reliably calculate facts. The results were again same in both cases and ended up with the similar Eigenface.

A hectic effort was deployed to get the single image recognition accuracy better by the use of SVM [28]. It utilized the idea of classification of images in the Eigenspace, but to no effort the result was same on the issue of small sample size.

3. Limitations of Related Work and Single Image Per Person Problem

The researchers have explored the field of face recognition in its vast aspects and have provided us with some limitations of the previous face recognition techniques highlighting single image problem.

a. The 2D face images must be altered into 1D vector where it leads to the far above ground dimensional vector gap, making it hard to calculate covariance matrix [28].
b. Eigenvectors of $(PC)^2A$ only reflect the variation between the rows of images. It omits variation between the columns of images which is also useful for recognition [33].
c. By projecting the 2D images directly, the irrelevant information stored in the image is also used which results in the use of many more coefficients for image representation [8].
d. Projection is measured in the spatial domain which is not a good option [8] because it results in the loss of spatial relationship between image pixels.
e. Principal Component Analysis provides less recognition accuracy when used with a single trained image.

f. Eigen decomposition cannot translate better in spatial domain. The length of the Eigenvector is much shorter [33].

Regarding the limitations of single image per person problem, this paper addresses three major aspects i.e., it handles the variation between the columns, irrelevant information is not projected because the image is not directly mapped and finally length of Eigenvector is increased to enhance recognition accuracy. To overcome the above mentioned problems, the LOG filter was selected as a pre-processing step to extract the information from each face image and represent the image in feature space using the four levels filtering of image. The advantage of using LOG is to extract useful information from the actual image which requires only one density to be performed at actual on the image. The mechanism of Laplacian [6] is basically spatial derivative of the image to 2nd order and resultant is isotropic measure in 2D form. After using LOG property, DCT is calculated. The use of such feature enriched image instead of the original image as an input for the 2 Dimensional Principal Component Analysis (2DPCA) increases the recognition accuracy significantly as per the experimental results conducted on the ORL datasets.

4. Laplacian Filtering in Image Processing

By analyzing the deterministic association connecting the lower-resolution images and the parallel high resolution images previously, the two hub methods named as Modified Laplacian Filter (MLF) and Intensity Correction (IC) were used. Such methods improve the resolution of the image so that the image [1] size can be enlarged with enriched information to be used later. The plain MLF is designed for appropriately restoring the occurrence components attenuated in the averaging and down-sampling humiliation process.

4.1. Discrete Cosine Transform

The DCT explicitly expresses many data points of the image by using the sum of the cosine values computed at varying frequencies. DCTs are significantly used nowadays to work on various applications from image compression to audio and video handling. It is, in fact, a method for numerical solution to the partial differential equation. On the contrary, it should be noted that the conceptual use of cosine values is far better than the sine values for compression purpose in an image. This is because older methods require fewer cosine values to compute a typical signal of an image. In some other conditions the concept of boundary conditions was also utilized to address the problem.

4.2. Gaussian Filtering

From the field of signal image processing and electronics, the Gaussian filter provides the inclination reaction as the Gaussian role. Gaussian filters are considered to give no go beyond to a step function key which reduces the time. This action is strongly attached to the fact that the Gaussian filter has the minimum possible cluster hindrance. Scientifically, a Gaussian filter modifies the input signal by density with a Gaussian function; this renovation is also known as the "Weierstrass transform".

4.3. Laplacian of Gaussian Filters

The Laplacian of Gaussian filter is used to extract the information from the edges of the exposed images and then the constructed images are provided with enriched information to extract good results.

5. Proposed Technique

The face recognition methods are basically categorized into three stages of processing the image i.e., the pre-processing stage, feature extraction and selection and finally the learning stage before being used in training and testing phase to compute the recognition accuracy. Presently, a lot of work on face recognition has been performed in the feature extraction and learning stages. The first stage is not considered much except in some of the few standard recognition techniques. Therefore, this paper proposes a pre-processing technique based on LOG and DCT for the representation of face images in a feature space along with enriched information as an input to PCA. Few main steps of the proposed technique are elaborated in detail as:

1. For an input image I the technique computes 4 level Laplacian of Gaussian image by varying values of sigma from 2-5 (for 4 levels). The image obtained from LOG is represented using C(u, v). Images after level 1 filtering are shown in Figure 1. Log of image will be computed as:

$$A(i,j) = I_i * \overline{V}^2 h_{\partial j}(r) \tag{1}$$

   where j= 2, 3…5 and I_i for input images, $A_{i,\,j}$ for LOG images. The reason for computing image filtering up to 4 levels lies in the fact that at each level image size is reduced to half of the previous level and finally gets reduced to maximum by 4th level. Further filtration will gather no useful information because of very small image size; therefore, level 5 filters were not used.
2. Next the paper computes the DCT of the input image and two dimensional DCT of all the four Laplacian of Gaussian images using equations 2 and 4 as shown in Figure 2. On the other hand, Figure 3 represents image after 3rd level filtering.

$$C_i = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos[\frac{(2x+1)u\pi}{2N}]\cos[\frac{(2y+1)v\pi}{2N}] \tag{2}$$

Where *f(x, y)*:

$$\alpha(u) = \left\{ \begin{array}{l} \sqrt{1/N}, u = 0 \\ \sqrt{2/N}, u = 1, 2, 3, \ldots, (N-1) \end{array} \right\} \quad (3)$$

Where N=Total number of images in a dataset, u represents Laplacian of Gaussian Image, v represents feature space of DCT images and C_i hold image after LOG and DCT filtering.

3. Select mid frequency coefficients of DCT representing low information contained in an image.
4. Construct the feature space by appending DCT coefficients of the original image and 4 LOG images.
5. Construct the vector (w), where w represents Eigenvectors for the images in database.
6. The covariance matrix is computed as D.

$$D = E[(X - \overline{X})(X - \overline{X})'] \quad (4)$$

Where $x = C_i$.

7. Perform the Eigen value decomposition as:

$$\begin{array}{l} J(X) = X^T D \\ X\ \{X_1 \ldots X_d\} = argmax\ J(X) \\ for\ j = 1 \ldots d \end{array} \quad (5)$$

where argmax $J(X)$ represents top Eigenvectors. Figure 4 defines the images after level 4 LOG filtering. The optimal projection axis $X_1 \ldots X_d$ is the orthonormal Eigenvectors of D corresponding to the first d largest Eigen values.

$$Y_k = I X_k \quad (6)$$

Where k = 1, 2, 3…d.

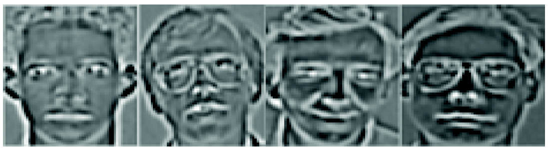

Figure 1. Images after level 1 filtering by LOG.

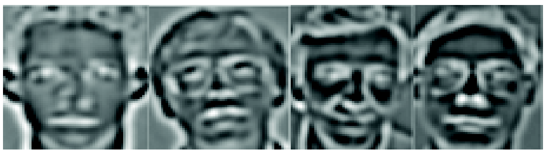

Figure 2. Images after level 2 filtering by LOG.

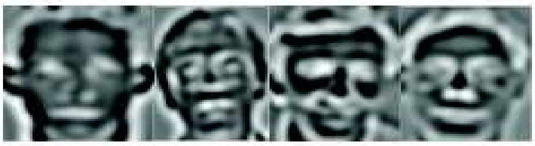

Figure 3. Images after level 3 filtering by LOG.

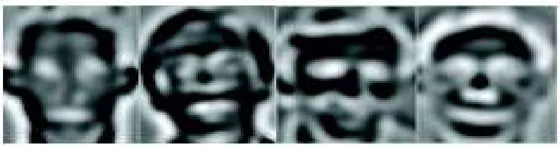

Figure 4. Images after level 4 filtering by LOG.

8. Compute the feature vector for each image of database by multiplying (w) with the selected Eigenvector as shown in Figure 5.

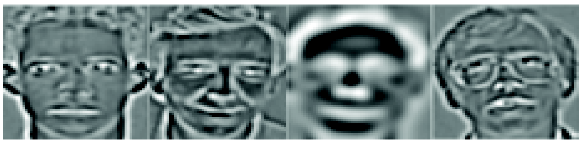

Figure 5. Images after filtering of LOG 4 levels and applying DCT.

The block diagram of the proposed system is shown in Figure 6.

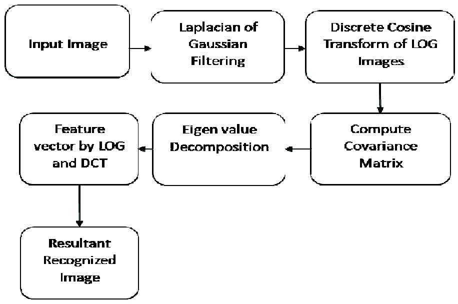

Figure 6. Functionality of the proposed system.

6. Advantages of Proposed System

The novelty of proposed technique is defined on the basis of constructive analysis performed on different datasets. The advantages of LOG (DCT) are listed below that outperform pervious methods while addressing the single image problem.

a. It works at the preprocessing stage that was not done in other methods.
b. LOG (DCT) handles variation between both rows and columns (opposed to previous methods which handle rows only), as a result of which the recognition accuracy increases.
c. LOG (DCT) projects the images after preprocessing stage which avoids use of more coefficients for image representation.
d. The technique increases the length of Eigenvector and hence enhancing the accuracy percentage of datasets.

7. Experimental Results

The experimental results were conducted on well known ORL [20], Yale [27], PIE [22], MSRA [19] and AR [2] datasets. The ORL dataset contains 400 images out of which 40 images were used as single image per person, where as Yale dataset contains 165 images with different illumination and lightening conditions. The test bed used for the experimental results in Table 1 is ORL standard database with all grey scale images and results used for comparison are results of those authors whose papers have been used for comparison.

Table 1. Describes the results with single image per person by changing the number of Eigenvectors from 10-40.

Eigenvectors	10	15	20	30	40
PCA[13]	42%	60%	70%	71%	79%
PROJECTION [26]	66%	68%	70%	80%	87%
LOG(DCT) (Proposed)	70%	74%	84%	90%	98%

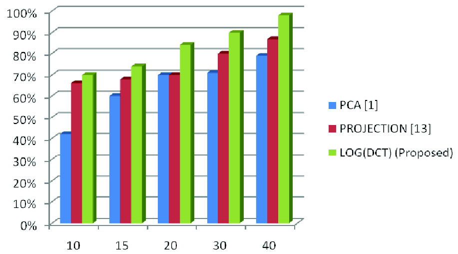

Figure 7. The results on the ORL face datasets.

7.1. Experimental Results on New Methods

The results of Table 2 compare the recognition accuracy of the (LOG) DCT with recent methods that address the single image per person problem of face recognition. The graphical representation of this comparison is shown in Figure 8. The test bed used for the experimental results in Table 2 is ORL standard database with all grey scale images and results used for comparison are results of those authors whose papers have been used for comparison.

Table 2. Describes the results on ORL datasets.

EIGENVECTORS	10	15	20	30	40
SPCA[18]	66%	68%	74%	78%	80%
SPCA+[18]	60%	72%	75%	76%	77%
PROJECTION [26]	66%	68%	70%	80%	87%
LOG(DCT) (Proposed)	70%	74%	84%	90%	98%

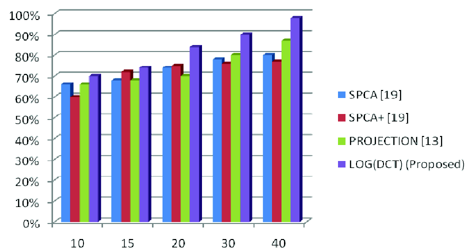

Figure 8. The results on the ORL face datasets.

7.2. Performance Results on Yale Dataset

Table 3 demonstrates recognition accuracy of Yale face dataset composed of 165 images. The table shows the accuracy of different facial recognition methods along with the proposed LOG (DCT). The test bed used for the experimental results in Table 3 is Yale face standard database with all grey scale images and results used for comparison are results of those authors whose papers have been used for comparison.

Table 3. The results on the Yale face datasets.

Methods	Accuracy
PCA	71.56% (119/165)
2DPCA	84.24% (139/165)
LOG(DCT) (Proposed)	93.93% (155/165)
$(PC)^2A$	69.70% (115/165)

Table 4 compares the recognition accuracy of single image face recognition using Laplacian of Gaussian and discrete cosine transform with 2DPCA and PCA such that the prime focus of accuracy percentage is on binary 2DPCA [28, 32], FR-using LBD, [12] ILLFR(DCT) [3] in LRD. The computed results were provided with a total of 165 images of different faces and the matched images against them along with the accuracy percentage. The test bed used for the experimental results of Table 4 is Yale face standard database with all grey scale images and results used for comparison are results of those authors whose papers have been used for comparison.

Table 4. The results on the Yale face datasets with comparison of B2DPCA, face recognition using (LBD), Illumination normalization FR (DCT) in LRD.

Methods	Accuracy
PCA	71.56% (119/165)
2DPCA	84.24% (139/165)
LOG(DCT) (Proposed)	93.93% (155/165)
B-2DPCA	80.70% (133/165)
FR-using(LBD)	89.70% (148/165)
ILLFR(DCT)in LRD	92.12% (152/165)

7.3. Performance Results on PIE Dataset

The PIE facial database comprises of 68 images with a total of 41,368 images from different angles. The images of this database were captured by synchronized cameras from 13 different directions under varying expression, illumination and pose variation as shown in Figure 9. This paper uses 150 images of each individual, 50 for training and 100 for testing the accuracy percentage.

Figure 9. Images of eight individuals from PIE database.

Table 5 shows the recognition percentage among Fisherfaces [29], Laplacianfaces, [26] and Eigenfaces [13] and LOG (DCT). The test bed used for the experimental results in Table 5 is PIE standard face database with all grey scale images and results used for comparison are results of authors whose papers have been referenced for comparison.

Table 5. The results on the PIE face datasets with comparison of Eigenfaces, Fisherfaces, Laplacian faces and proposed method LOG (DCT).

Methods	Accuracy
Eigenfaces	80.66% (121/150)
Fisherfaces	94.60% (142/150)
Laplacian Faces	95.33% (143/150)
LOG(DCT) (Proposed)	97.33% (146/150)

7.4. Performance Results on MSRA Dataset

The MSRA face image database was collected at Microsoft Research Asia and it is composed of 12 individual images collected in two sessions with different background and illumination conditions. All the faces of this database are frontal. In the analysis process of accuracy percentage, session 1 with 60 images was used at training side and session 2 with 80 images was used at testing side in order to prove the recognition percentage. Figure 10 shows 8 individual images of the MSRA database. The images in the first row were used for training and the second row images were used at testing side.

Figure 10. Images of eight individuals from MSRA database.

The images in the first row are taken in first session; second row shows the images in second session.

Table 6 finally shows recognition percentage among Fisherfaces [29], Laplacianfaces, [26] and Eigenfaces, [13] 2DPCA [28], B-2DPCA, FR-using (LBD), ILLFR (DCT) in LRD and LOG (DCT). The test bed used for the experimental results in Table 6 is MSRA face standard database with all grey scale images and results used for comparison are results of authors whose papers have been referenced for comparison.

Table 6. The results on the MSRA face datasets withcomparison of Eigenfaces, Fisherfaces, Laplacian faces and proposed method LOG (DCT), FR-using (LBD), 2DPCA, B-2DPCA etc.

Methods	Accuracy	Error Percentage
Eigenfaces	63.75% (51/80)	36.25%
Fisherfaces	75.00% (60/80)	25.00%
2DPCA	83.74% (67/80)	16.25%
B-2DPCA	88.75% (71/80)	11.25%
Laplacian Faces	92.50% (74/80)	07.50%
FR-using(LBD)	93.75% (75/80)	06.25%
ILLFR(DCT) in LRD	95.00% (76/80)	05.00%
LOG(DCT) (Proposed)	96.25% (77/80)	03.75%

7.5. Performance Results on AR Dataset

The AR face database was collected at Purdue University with a total of 4,000 images of 126 people (70 men and 56 women). Table 7 provides recognition accuracy percentage of AR dataset on 1000 frontal face images, out of which 100 were used at training side (60 men and 40 women) and 900 on testing side of the algorithm. Images cropped as frontal faces with variation in facial expressions, pose variation and illumination conditions. The test bed used for the experimental results in Table 7 is standard AR database with all grey scale images and results used for comparison are results of those authors whose papers have been referenced for comparison.

Table 7. The results of AR face datasets with comparison of Eigenfaces, Projection, B-2DPCA, ILLFR (DCT) in LRD FR-using (LBD) and Proposed method LOG (DCT).

Methods	Accuracy	Error Percentage
Eigenfaces	74.44% (670/900)	25.56%
Projection $(PC)^2A$	77.78% (701/900)	22.22%
B-2DPCA	86.11% (775/900)	13.89%
ILLFR(DCT) in LRD	90.55% (815/900)	09.45%
FR-using(LBD)	94.44% (850/900)	05.56%
LOG(DCT) (Proposed)	95.55% (860/900)	04.45%

Table 8 provides time comparison of the proposed method with other conventional methods on AR face database. As AR is hard dataset to test the algorithm time but it can change to drastic amount depending upon the machine and considering the clock cycles mechanism as a medium for computing the feature and recognition time.

Table 8. Time comparison of the proposed method with other conventional methods on AR face database.

Methods	Features Time	Recognition Time
Eigenfaces	129.56	16.2
Projection $(PC)^2A$	40.07	05.40
2DPCA	8.32	01.08
LLFR(DCT) in LRD	2.095	0.324
FR-using(LBD)	2.066	0.157
LOG(DCT) (Proposed)	2.032	0.079

7.6. Overall Performance Results on ORL, Yale, PIE, MSRA, AR Datasets

Table 9. Comparsion table for overall results of LOG(DCT).

Methods	Accuracy% ORL Data Set	Error%	Accuracy% Yale Data Set	Error%	Accuracy% PIE Data Set	Error%	Accuracy% MSRA Data Set	Error%	Accuracy% AR Data Set	Error%
Eigenfaces	N/A	N/A	N/A	N/A	80.66%	19.34%	63.75%	36.25%	74.44	25.56%
Fisherfaces	N/A	N/A	N/A	N/A	94.60%	05.40%	75%	25%	N/A	N/A
2DPCA	N/A	N/A	84.24%	15.76%	N/A	N/A	83.74%	16.25%	N/A	N/A
PCA	79%	21%	71.56%	20.44%	N/A	N/A	N/A	N/A	N/A	N/A
Projection$(PC)^2A$	87%	13%	69.70%	30.30%	N/A	N/A	N/A	N/A	77.78%	22.22%
B-2DPCA	N/A	N/A	80.70	19.30%	N/A	N/A	88.75%	11.25%	86.11%	13.89%
Laplacian Faces	N/A	N/A	N/A	N/A	95.33%	04.67%	92.50%	07.50%	N/A	N/A
FR-using(LBD)	N/A	N/A	89.70%	10.30%	N/A	N/A	93.75%	06.25%	94.44%	05.56%
ILLFR(DCT) in LRD	N/A	N/A	92.12%	8.88%	N/A	N/A	95%	05%	90.55%	09.45%
LOG(DCT) (Proposed)	**98%**	**2%**	**93.93%**	**06.07%**	**97.33%**	**2.67%**	**96.25%**	**03.75%**	**95.55%**	**04.45%**

8. Computation Time

The computation time for single image face recognition using LOG and DCT is presented. The experimental results were carried out on Pentium IV machine with 3.2 GHz processor, 2GB RAM and Matlab 2008a. It takes 2.032 seconds for database training and computation of features and 0.08 seconds for recognition of input image which is better than other conventional techniques used for computing results. Since the computational time gives a real low complexity for the algorithm, so it can be deployed in real environment.

9. Conclusion

Paper concludes by achieving high recognition accuracy for single image per person problem addressed with pre-processing technique called LOG (DCT) PCA. It has many advantages over the conventional methods as it stores the input image with more useful information than $(PC)^2A$. Secondly, it is better in terms of recognition accuracy as compared to PCA [3] and $(PC)^2A$ [15].

Finally, there are some major aspects that really outperform $(PC)^2A$ as by the use of Laplacian of Gaussian discrete cosine transforms for face recognition. The filter provides a total of eight images at the two levels of LOG and DCT, all enriched with information of the input face that helps in increasing the recognition accuracy.

10. Future Work

The proposed algorithm of single image face recognition is tested on concept of Laplacian of Gaussian and Discrete Cosine transform. For future work this idea can be merged up with multi-resolution transforms in the form of surfacelets, curvelete and contourlets [17] etc., and experimental results can be performed on colored image datasets or 3D images.

References

[1] Arandjelovic O. and Cipolla R., "A Methodology for Rapid Illumination-Invariant Face Recognition using Image Processing Filters," *Computer Vision and Image Understanding*, vol. 113, no. 2, pp. 159-171, 2009.

[2] AR Database, available at: http://cobweb.ecn.purdue.edu/~aleix/aleix_face_DB.html, last visited 2009.

[3] Batur A. and Hayes M., "Linear Subspace for Illumination, Robust Face Recognition," *International Journal of Computer Vision*, vol. 57, no. 1, pp. 49-66, 2004.

[4] Belhumeur P., Hespanha J., and Kriegman D., "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," *IEEE Transaction Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, 1997.

[5] Belkin M. and Niyogi P., "Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering," *in Proceedings of Advances in Neural Information Processing Systems*, pp. 585-591, 2001.

[6] Belkin M. and Niyogi P., "Using Manifold Structure for Partially Labeled Classification," *in Proceedings of Conference Advances in Neural Information Processing System*, pp. 1-8, 2002.

[7] Brand M., "Charting a Manifold," *in Proceedings of Advances in Neural Information Processing Systems*, pp. 961-968, 2003.

[8] Brunelli R. and Poggio T., "Face Recognition: Features Versus Templates," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 10, pp. 1042-1052, 1993.

[9] Chen S., Liu J., and Zhou Z., "Making FLDA Applicable to Face Recognition with One Sample per Person," *Pattern Recognition*, vol. 37 no. 7, pp. 1553-1555, 2004.

[10] Chung F., *Spectral Graph Theory*, American Mathematical Society, 1997.

[11] Hammond D. and Simoncelli E, "Nonlinear Image Representation via Local Multiscale Orientation," *Technical Report Courant Institute*, 2005.

[12] He X., Yan S., Hu Y., Niyogi P., and Zhang H., "Face Recognition Using Laplacianfaces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 3, pp. 328-340, 2005.

[13] Kirby M. and Sirovich L., "Application of the Karhunen-Loève Procedure for the Characterization of Human Faces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 1, pp. 103-108, 1990.

[14] Liu J., Chen S., Zhou Z., and Tan X., "Single Image Subspace for Face Recognition," *in Proceedings of the 3rd International Conference on Analysis and Modelling of Faces and Gestures*, Berlin, pp. 205-219, 2007.

[15] Lu X., "Image Analysis for Face Recognition," *in Proceedings of Personal Notes, Department of Computer Science and Engineering*, USA, pp. 1-37, 2003.

[16] Loog M., Duin R., and Haeb-Umbach R., "Multiclass Linear Dimension Reduction by Weighted Pairwise Fisher Criteria," *IEEE Transaction Pattern Analysis Machine Intelligence*, vol. 23, no. 7, pp. 762-766, 2001.

[17] Majumdar A. and Bhattacharya A., "A Comparative Study in Wavelets, Curvelets and Contourlets as Feature Sets for Pattern Recognition," *The International Arab Journal of Information Technology*, vol. 6, no. 1, pp. 47-51, 2009.

[18] Majumdar A. and Ward R., "Single Image per

Person Face Recognition with Images Synthesized by Non-Linear Approximation," *in Proceedings of 15th IEEE International Conference on Image Processing*, pp. 2740-2743, 2008.
[19] MSRA Database, available at: http://research.microsoft.com/en-us/projects/msrammdata, last visited 2009.
[20] ORL, available at: http://www.uk.research.att.com/ facedatabase.html, last visited 1992.
[21] Park U., Tong Y., and Jain A., "Face Recognition with Temporal Invariance: A 3D Aging Model," *in Proceeding of 8th IEEE International Conference on Automatic Face and Gesture Recognition*, pp. 1-7, 2008.
[22] PIE Database, available at: http://www.ri.cmu.edu/research-project-detail.html?project-id=418 &menu-id=261, last visited 2011.
[23] Tana X., Chena S., Zhou Z., and Zhang F., "Face Recognition from A Single Image per Person: A Survey," *Journal Pattern Recognition*, vol. 39, no. 9, pp. 1725-1745, 2006
[24] Wang J., Plataniotis K., and Venetsanopoulos A., "Selecting Discriminant Eigenfaces for Face Recognition," *Pattern Recognition Letters*, vol. 26, no. 10, pp. 1470-1482, 2005.
[25] Wiskott L., Fellous R., Kruger N., and Malsburg C., "Face Recognition by Elastic Bunch Graph Matching," *IEEE Transaction of Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 775-779, 1997.
[26] Wu J. and Zhou Z., "Face Recognition with one Training Image per Person," *Pattern Recognition Letters*, vol. 23, no. 14, pp. 1711-1719, 2002.
[27] Yale University Face Database, available at: http://cvc.yale.edu/projects/yalefaces/yalefaces.html, last visited 1997.
[28] Yang J., Zhang D., Frangi A., and Yang J., "Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition," *IEEE Transaction of Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, pp. 131-137, 2004.
[29] Yang M., "Kernel Eigenfaces vs. Kernel Fisherfaces: Face Recognition Using Kernel Methods," *in Proceedings of 5th IEEE Int'l Conference Automatic Face and Gesture Recognition*, pp. 215-220, 2002.
[30] Yu H. and Yang J., "A Direct LDA Algorithm for High-Dimensional Data with Application to Face Recognition," *Pattern Recognition*, vol. 34, no. 10, pp. 2067-2070, 2001.
[31] Yuen P. and Lai J., "Face Representation Using Independent Component Analysis," *Pattern Recognition*, vol. 35, no. 6, pp. 1247-1257, 2002.
[32] Zhang D., Chen S., and Zhou Z., "A New Face Recognition Method Based on SVD Perturbation for Single Example Image per Person," *Applied Mathematics and Computation*, vol. 163, no. 2, pp. 895-907, 2005.
[33] Zhang D. and Zhou Z. "Letters: (2D)2PCA: Two-Directional Two-Dimensional PCA for Efficient Face Representation and Recognition," *Neurocomputing*, vol. 69, no. 1-3, pp. 224-231, 2005.

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