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An Improved Face Recognition Using Neighborhood Defined Modular Phase Congruency Based Kernel PCA

Mr. G.D. Basavaraj
M.Tech Student, Department of EEE, Tiruparthi, Andhra Pradesh, INDIA-515002

Dr. G. Umamaheswara Reddy
Associate Professor, Department of ECE, SVUCE Tiruparthi, Andhra Pradesh, INDIA-515002

***Abstract*—A face recognition algorithm based on NMPKPCA algorithm presented in this paper. The proposed algorithm when compared with conventional Principal component analysis (PCA) algorithms has an improved recognition Rate for face images with large variations in illumination, facial expressions. In this technique, first phase congruency features are extracted from the face image so that effects due to illumination variations are avoided by considering phase component of image. Then, face images are divided into small sub images and the kernel PCA approach is applied to each of these sub images. but, dividing into small or large modules creates some problems in recognition. So a special modulation called neighborhood defined modularization approach presented in this paper, so that effects due to facial variations are avoided. Then, kernel PCA has been applied to each module to extract features. So a feature extraction technique for improving recognition accuracy of a visual image based facial recognition system presented in this paper.**

***Key-words*—** *face recognition, phase congruency, modularization, kernel PCA, feature extraction.*

I. INTRODUCTION

A facial recognition system is a kind of biometric system for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. Face recognition is a difficult task because of similar shape of faces combined with the numerous variations between images of same face. The image of a face changes with facial expression, age, view point, illumination conditions etc. The task of the face recognition system [1] is to recognize a face in a manner that is as independent as possible of these image variations.

Face recognition is one of the most important of image analysis, its prime applications being recognition of face for the purpose of security. The main objective of this work is to improve the accuracy of face recognition subjected to varying facial expressions, illumination and head pose. Initially, PCA method [2],[3] has been a popular technique for facial image recognition. But this technique is not useful when the illumination and expression of the image vary considerably. Further, modular PCA method [4],[5] which is an extension of conventional PCA method, has been discussed.In this method the face images are divided into smaller images and the PCA method is applied on each of them. In this method, effects due to local variations are nullified. Consequently, Phase congruency based PCA [6], [7] methods has been implemented. In this method phase congruency features extracted from image then PCA applied to the image. In this approach, illumination effects are nullified because here phase component of image is considered. Consequently, MPPCA [8] method has been presented. In this method, phase congruency features [9] extracted from image then, modularization done and PCA is applied to each module image. Modularizing the images would help to localize these variations, provided the modules created are sufficiently small. But in this process, a large amount of dependencies among various neighboring pixels might be ignored. This can be countered by making the modules larger, but this would result in an improper localization of the facial variations. In order to deal with this problem, a module creation strategy has been presented in this paper which considers additional pixel dependencies across various sub-regions. This helps in providing additional information that could help in improving the recognition accuracy. Here, kernel PCA [10], [11], [12] is applied to each module to extract features So, the main difference between PCA and NMPKPCA [13] is, by using PCA we cannot recognize the images if variations caused by illumination, expressions in images. So recognition rate is poor in case of PCA. But by using NMPKPCA we can recognize the images even in the presence of illumination and expression variations. So recognition rate is improved by using NMPKPCA approach in comparison with PCA approach.

The paper is organized as follows. The importance of phase congruency and its evaluation is explained in section II. The importance of modularization and need for neighborhood defined modularization is discussed in section III. The procedure to find weights of each module is presented in section IV. Simulation results by considering different images with variations in illumination and expression are given in section V and finally conclusion is presented in section VI.

II. PHASE CONGRUENCY

Phase congruency [6], [7] provides a measure that is independent of the overall magnitude of the signal making it invariant to variation in illumination and contrast. The phase component [9] is more important than the magnitude component because phase component is independent of illumination. So by applying PCA based recognition technique on the phase spectrum of images yield better accuracy than magnitude spectrum of images.

A. Phase congruency for 1-D signal

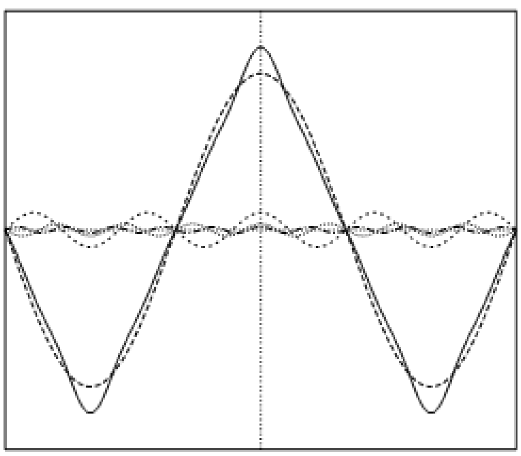


Fig 1: Periodic triangular wave with its Fourier components

First consider a 1-D signal, by applying Fourier transform the signal is represented by sum of sinusoidal in frequency domain. From Fig.1 it can be observed that all Fourier components are meeting at edges. Hence, all Fourier components have same phase at edges. So, phase congruency is maximum at edges. At edges it can be observed that Energy is also maximum because all Fourier components are meet at edges. So Phase congruency is directly proportional to Energy [14], [15]. To make the phase congruency dimensionless it is normalized with sum of amplitudes of all Fourier components. If sum of all Fourier components amplitudes are so small then phase congruency become infinity i.e. a very large value .To avoid that problem a small value is added to the denominator. Hence, phase congruency equation is given as

$$PC(x)=\frac{E(x)}{\sum_n A_n+\varepsilon} \qquad (1)$$

In general , noise is added to signal or image processing. So, in order to compensate noise effects filtering techniques is used. Here , log gabor filter[6] is used to reduce the noise effects.

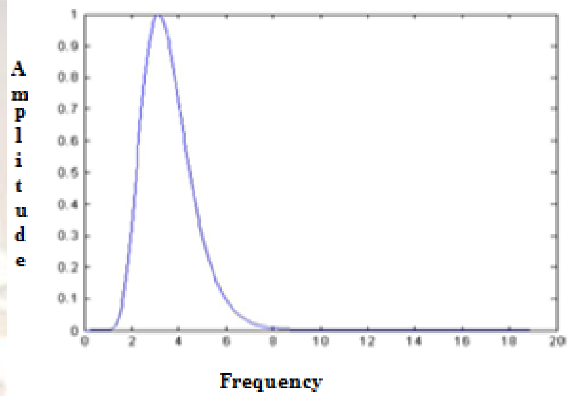


Fig.2: example of log-Gabor transfer function

B. Calculation of Phase Congruency for Images

The transfer function of log-Gabor is of the form

$$G(w)=e^{\left(-\log\left(\frac{w}{w_c}\right)^2\right)/\left(2\left(\log\left(\frac{p}{w_c}\right)\right)^2\right)} \qquad (2)$$

Where$w_c$the filter's center frequency is $p/w_c$is kept constant for variousw_c. Fig. 2 illustrates an example of a log-Gabor transfer function.

The transfer function of 2-D log Gabor filter in the angular direction, constructed by using Gaussian function is given by

$$G(\emptyset)=e^{(-(\emptyset-\emptyset_0)^2)/(2\sigma_\emptyset{}^2)} \qquad (3)$$

Where $\emptyset_0$is orientation of the filter,$\sigma_\emptyset$ is the standard deviation of the Gaussian function. Eight orientations and 4 scales are chosen here. Then, divide the filter into even symmetric and odd-symmetric components at a given scale and orientation is given byH_{no}^e,H_{no}^o.then, the response vector can be obtained by convolving the image I(x,y) with a bank of 2-D log-Gabor filters, is given by

$$[e_{no}(x,y),o_{no}(x,y)]=[I(x,y)*M_{no}^e,I(x,y)*M_{no}^o] \qquad (4)$$

At a given scale and orientation, the amplitude of the response can be computed by

$$A_{no}=((e_{no}\ (x,y)^2+o_{no}\ (x,y)^2))^2 \qquad (5)$$

phase congruency of the image calculated over various scales and orientations given by

$$PC(x.y)=\frac{\sum_o((\sum_n e_{no}\ (x,y))^2+(\sum_n o_{no}\ (x,y))^2)^{1/2}}{\sum_o\sum_n A_{no}\ (x,y)+\varepsilon} \qquad (6)$$

In general, Phase congruency lies between 0 and 1.

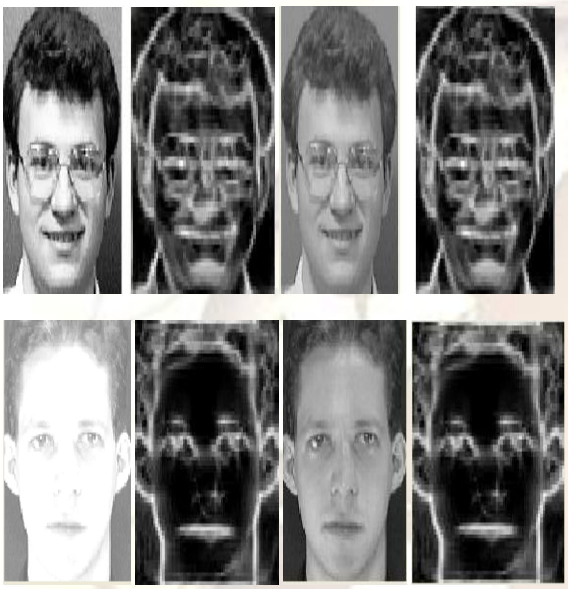


Fig.2: phase congruency images for various intensities

III.MODULARISATION

Modularization means dividing the image into small number of modules. In this method, local variations in face images are recognized.But, there is a conflict that whether dividing the image into small modules or large modules. If the image is divided in to very smaller modules, a large amount of sub region information is lost because of dependencies among various neighboring pixels are ignored .this problem can be overcome by increasing module size i.e. making the modules larger. But, due to thismodularizationthe local variations in face images are not perfectly recognized. So, in order to overcome these problems, a new modularization technique called neighborhood defined modularization technique is implemented.

A. NEIGHBORHOOD MODULARIZATION

Dividing the images into smaller or larger modules create some problems in recognition. Here, advantages of both modularizations [4] are implemented. First, divide the image into large modules called sub regions. Then, divide the each sub region into small number of modules. Then, by merging neighborhood small modules in a sub region, large numbers of modules are created in a sub region. So, by using this region based modularization feature extraction approach local facial variations caused by expression variations in image can be dealt more effectively.

In general, face images are captured by webcam and the face images are of size 1024 x1024. So, in order to process this image it takes a lot of time. So, to minimize the processing speed, the face images are normalized to a size of 64×64 in our experiments. Normalizing the image in terms of even powers of 2 also helps in dividing an image into modules of same size in a modular approach for face recognition. Modular PCA technique divides the image into non overlapping sub-images. Then PCA is applied to each module. Several experimental results have been observed with different modules of size of 4×4, 8×8 and 16×16 on face images of size 64 ×64. Finally, it is observed that, recognition accuracy is maximum when the image is divided into sub-regions of size 8× 8. With Large module size (16×16),the local variations of image is poorly recognized. In case of small module size (4×4),the dependencies among neighboring pixels are ignored. So, the sub-region information content is lost. Finally, it is concluded that sub-region information must be considered because it occupies some facial feature information. Hence, in the implemented neighborhood defined modularization approach, several 8 ×8 modules are created by combining neighborhood modules of size 4 ×8 modules in a large region of size 16 ×16 in a 64 ×64 face image.

Steps followed for the implementation of Neighborhood defined modularization technique for an image of sizeM×M dimensions are given below:

1. Divide each image into non overlapping large modules of (M/m) × (M/m) size to get (m×m) number of large modules.

2. Divide each large module of size (M/m)×(M/m) into modules of size(M/(m×i))×(M/(m×j)), where (i×j) is the number of small modules within a neighborhood.

3. Then, by merging (i×j) number of small modules in neighborhood, a total of R modules are created according to the relation=(i×j)!/(k!(i×j-k))! where k is the number of small modules to be merged.

IV. FEATURE EXTRACTION

Initially, PCA [6] technique is used in order to extract features of an image. PCA is a linear subspace approach, which can not capture the relation among more than two variables. Because PCA is directly applied to image. So PCA, can not capture the variations caused by expressions and other variables. In order to deal with this problem nonlinear space [5] method is used. The non linear relationship among pixels is captured using kernel PCA [10] by projecting the data into higher dimensional spaces. .

A.KERNEL PCA

Input: Data X={x_1, x_2, …, x_l} in *n*-dimensional space.
Process: Mean of the data is given by

$$m = \frac{1}{l}\sum_{k=1}^{l} x_k \quad (7)$$

But mean not only enough to extract features.so,co variance matrix C is given by

$$C = \sum_{j=1}^{l} x_j\, x_j^T \quad (8)$$

The eigen vectors corresponding to covariance matrix is given by
CV=ΛV(9)
Here data is projected in to higher dimentional spaces

$$\Phi : X \rightarrow H$$

Where X stands for input space and H stands for feature space.then eigen values and eigen vectors of covariance matrix is

$$C_\Phi V_\Phi = \lambda_\Phi V_\Phi \quad (10)$$

So feature extraction can be done by finding eigen values and eigen vectors and weights to each module as follows

1.Kernel matrix $K_{i,j}= k(x_i,x_j)$; $i,j=1,\dots, l$.

$$k(x_i,x_j)=\exp\left(\frac{(-||(x_i-x_j)||^2}{\sigma}\right) \quad (11)$$

2.Then,find kernel centered matrix .here i,j are unity matrices of module size

$$K' = K - \frac{1}{l}\, j.j'.K - \frac{1}{l}\, K.j.j' + \frac{1}{l^2}(j'.K.j).j.j' \quad (12)$$

3 Eigen values,eigen vectors computed for kernel centre matrix

$$[W,\Lambda] = \mathrm{eig}K' \quad (13)$$

4 Normalise the eigen vectors

$$\propto^{(j)} = \frac{1}{\sqrt{\Lambda_j}} W_j \quad (14)$$

5 Multiply normalised eigen vectors with kernel centre matrix to get weights

$$\mathbb{x}_j = \left(\sum_{i=1}^{l} \propto_i^{(j)}\; k(x_i, x)\right)_{j=1}^{k} \quad (15)$$

ALGORITHM:

The Algorithmic steps followed in the training procedure are listed below:

1) Capture face image and calculate the phase congruency according to the procedure discussed in Section II.
2) Divide phase congruency image in to small modules according to the procedure discussed in Section III.
3) After Creating modules, process each set of modules separately.
4) Obtain the kernel matrix for each module according to the procedure described in section IV.
5) For each module, Apply KPCA and obtain the weights for all the individual modules in that region.

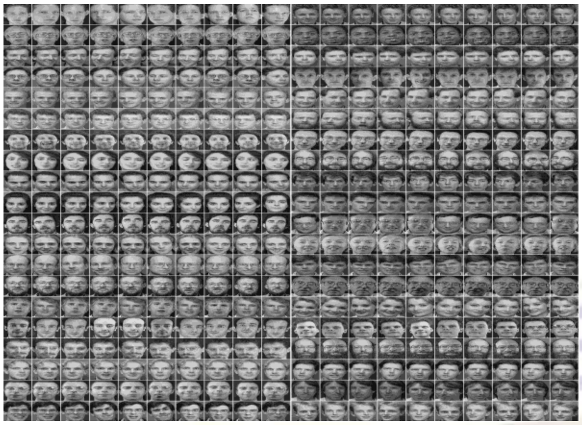
Fig.3: Block diagram for face recognition technique

The following steps are involved in the classification of a test image:
1) Calculate the phase congruency features of the test image.
2) Create the modular regions by neighborhood defined modularization.
3) Apply KPCA to each module and calculate the weights for each individual module using eigen vectors and kernel matrix.
4) By using a minimum distance classifier classify each module basedon the generated weights from the training and the testing phase.

V.SIMULATION RESULTS

In this chapter, recognition accuracy of PCA and NMPKPCA algorithms is compared. Consider ‘22’ individual images and create database such that ‘11’ images of each individual present in database. GUI is used in order to make process easier.

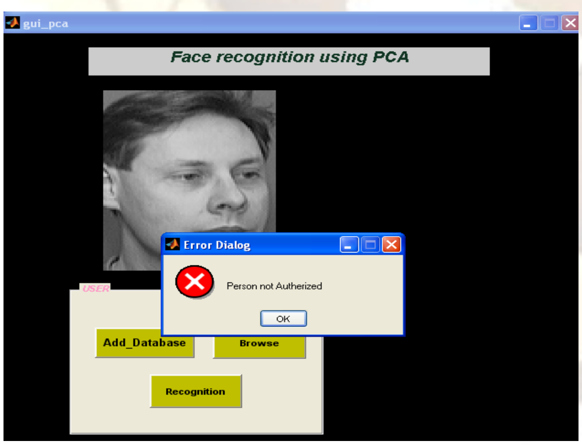
DATA BASE IMAGES



Consider test images which may not exactly same as images in database .first, PCA algorithm is applied and observed that the test image not recognized because the test image have some variations when compared with database image. Hence, PCA recognize images if the test image is exactly same as database image. But, by using NMPKPCA, the recognition rate is good even test images which are not exactly same as database images, in terms of illumination and expressions .

A.FACE RECOGNITION USING PCA

Let us consider test image different from database image. So even small variations in face the pixel values are changed nonlinearly. So, recognition rate is poor by using PCA under the variations in illumination and expressions.



In PCA, even small variations in face are not recognized because PCA is directly applied to whole image. So, a small variation in face causes change in pixel values and finally feature values also changed. So, face recognition becomes difficult under varying expressions.

Fig.4: Face recognition using PCA.

B.FACE RECOGNITION USING NMPKPCA ALGORITHM:

In NMPKPCA, to recognize image each image undergo 4 phases. First phase is taking input image, second phase is phase congruency, third phase is modularization, and fourth phase is recognition, the process described below.

a) *INPUT IMAGE*

capture one image whether the image is in database or not. Here, database consists of images and consider a test image with some changes in illumination or expressions or same image as like as data base image. So, take input image from webcam or any cam is the first step in face recognition

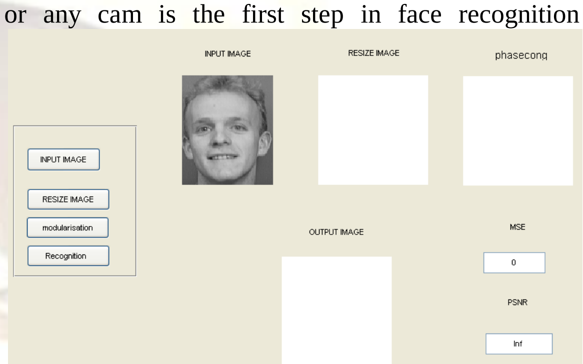


Fig.5: Input image from test images.

b)PHASE CONGRUENCY

After taking the input image, phase congruency calculated to image as described in section 2.phase congruency means extracting the phase features of image such that to make the face recognition system independent of illumination. In future, observed that even changes in illumination the phase congruency image not changed.

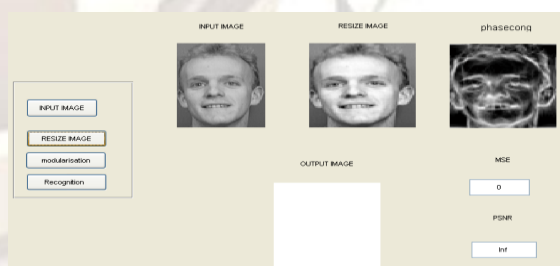


Fig.6: Phase congruency image for test image.

c)MODULARISATION

After caluculating phase congruency, apply modularisation technigue as described in section 3.Here, modularisation is applied to phase congruency image so that local variations in face image is perfectly recognised. But normal modularization create some problems.so a special modulation called neighborhood defined modularization is defined here.

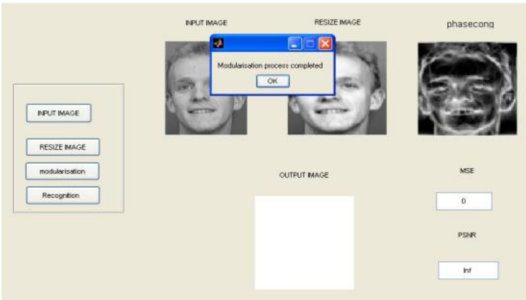


Fig.7: Modularisation process

d)*RECOGNITION*

After modularisation,then apply kernel PCA to each module to extract features of each module and finally caluculate the weights of each module by using karnel matrix and algorithm as described in section IV.from this recognition , finding the MSE and PSNR values between test image and database image and finally conclude that up to these variations algorithm works.

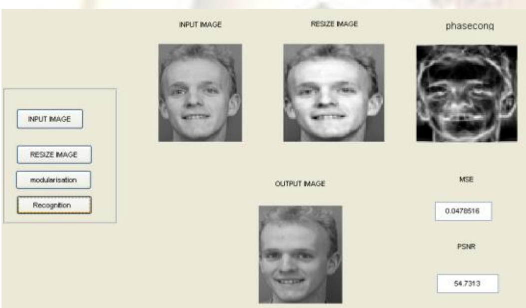


Fig.8: Recognized image by applying NMPKPCA.

So the same test image is recognized using NMPKPCA even some variations in face image, so recognition accuracy is improved by using NMPKPCA compared with PCA.

I) *FACE RECOGNITIONUNDER DIFFERENT ILLUMINATIONS:*

Consider a face image with different illuminations.let k be the illumination parameter then by varying k at different values observe the output results of face recognition.

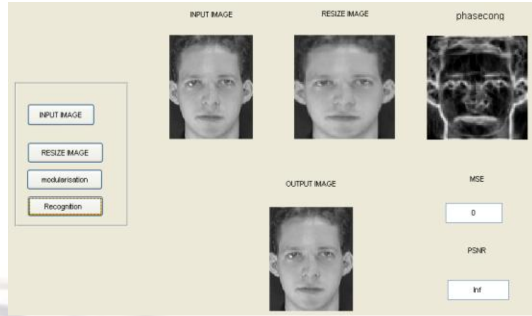


Fig 8: face recognition when k=0

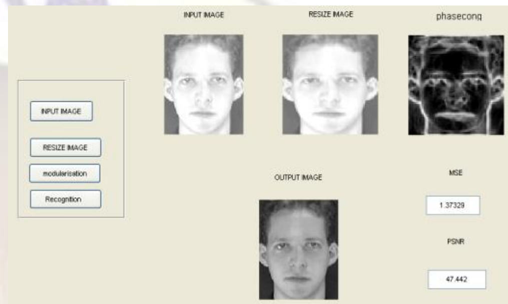


Fig 9: face recognition when k=0.1

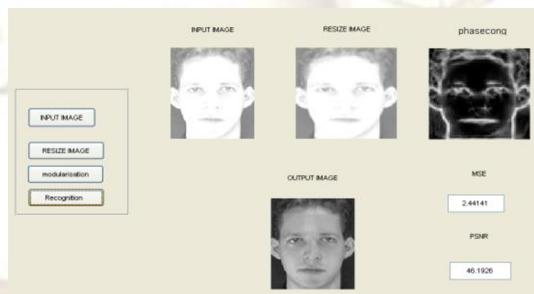


Fig 10: face recognition when k=0.2

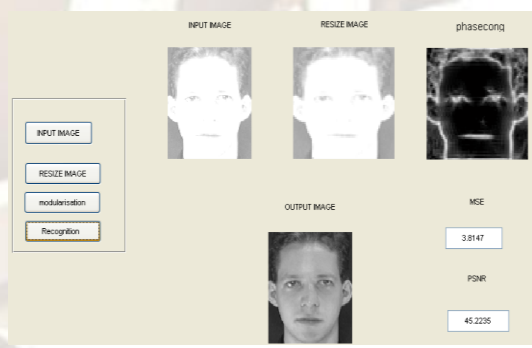


Fig 11: face recognition when k=0.3

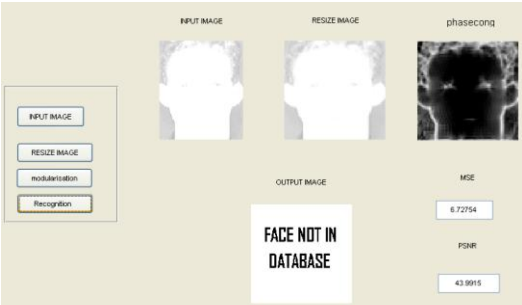


Fig 12: face recognition when k=0.4

The values for MSE, PSNR for different values of k are listed below:

k	MSE	PSNR
0.1	1.37329	47.442
0.2	2.44141	46.1976
0.3	3.8147	45.2235
0.4	5.64063	44.3742.

Table 5.1: Values of MSE, PSNR for different values of illumination parameter k

I) *FACE RECOGNITIONUNDER DIFFERENT EXPRESIONS*

Consider several images with variations in face expressions and apply them to face recognition system and note down the MSE and PSNR values for different expressions.

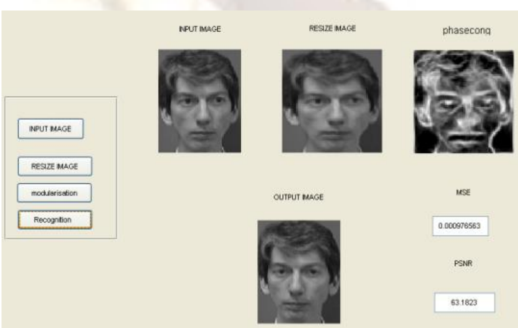


Fig 13: face recognition under variations in expression

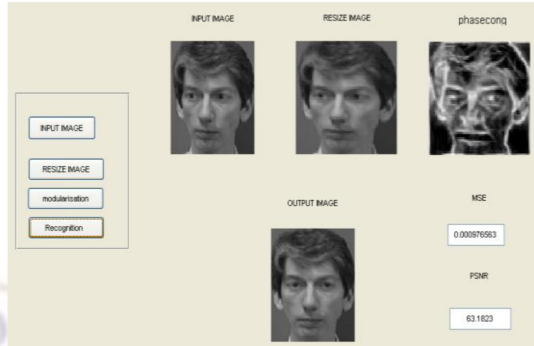


Fig 14: face recognition under variations in expression

This algorithm works up to some variations in expressions. The variations are calculated by PSNR & MSE.

PSNR	MSE
51.879	0.177979

Table 5.2: Values of MSE, PSNR under varying expession

This algorithm works up to some variations in illumination. The variations are calculated by PSNR & MSE.

PSNR	MSE
44.3742	5.64063

Table 5.3: Values of MSE, PSNR under varying illumination

VI. CONCLUSION

A face recognition technique using neighborhood defined modular phase congruency-based kernel PCA (NMPKPCA) algorithm is presented in this paper. Initially, PCA methodis used for face recognition.. since small changes in expressions and illumination the pixel values are changed nonlinearly. In PCA, the algorithm directly applied to image means nonlinear variations are not recognized. Hence, recognition rate is poor in case of PCA. So, conclude that the algorithm not capture the non linear variations. Consequently, NMPKPCA method, which is an extension of the PCA method for face recognition has been implemented. The NMPKPCA method performs better than PCA method under the conditions of large variations (k=.41) in illumination and expression. In the first phase, Phase congruency applied to the image so that recognition system should become independent of illumination. After acquiring phase congruency image, apply modularization so that local variations are also

recognized. Hence recognition rate is improved. So, for face recognition the NMPKPCA method can be used as an alternative to PCA method. In particular, the NMPKPCA method will be useful for identification systems subjected to large variations in illumination and facial expressions.
In future, Implement a face recognition system to recognize color images by using NMPKPCA algorithm and find the values of MSE and PSNR for variations in illumination and expressions.

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