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Research Paper

FACE RECOGNITION BY PHASE CONGRUENCY MODULAR KERNEL PRINCIPAL COMPONENT ANALYSIS

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This paper presents novel modular kernel Eigen spaces approach to implement on the phase congruency images. Smaller sub-regions from a predefined neighbourhood within the phase congruency images of the training samples are merged to obtain a large set of features. These features are then projected into higher dimensional spaces using kernel methods. The proposed localized nonlinear feature selection procedure helps to overcome the bottlenecks of illumination variations, partial occlusions, expression variations and variations due to temperature changes that affect the face recognition techniques. Databases are used for experimentation and evaluation of the proposed technique. Also, a decision level methodology is presented which along with the feature selection procedure has outperformed various other face recognition techniques in terms of recognition accuracy.

Keywords: Feature extraction, Kernel methods, Phase congruency

INTRODUCTION

Face recognition is one of the most important applications of image analysis, its prime applications being recognition of individuals for the purpose of security. It is one of the most non obtrusive biometric techniques. Even though face recognition technology (Zhao *et al*., 2003) has moved from linear subspace methods (Belhumeur *et al*., 1997)—Eigen and Fisher faces (Turk and Pentland, 1991; Pentland *et al*., 1994) to nonlinear methods such as kernel principal component analysis (KPCA) and kernel Fischer discriminated analysis (KFDA) (Huang *et al*., 2004; Yang *et al*., 2002; Yang, 2002; and Yang *et al*., 2004), many of the problems are yet to be addressed.

Feature-based face recognition techniques (Zhou and Wei, 2006; and Shen and Bai, 2004)

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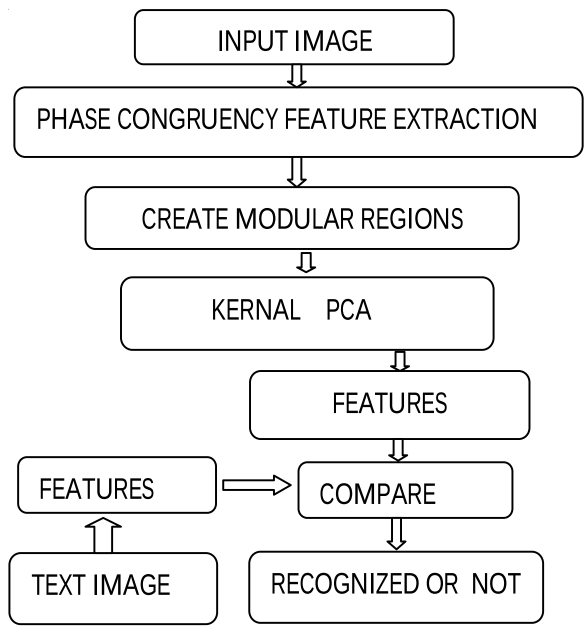
have demonstrated the capability of invariance to facial variations caused by illumination and have achieved high accuracy rates. To make the recognition process illumination invariant, phase congruency feature maps are used instead of intensity values as the input to the face recognition system. The feature selection process presented in this paper is derived from the concept of modular spaces (Gottumukkal and Asari, 2004; Martinez, 2000; and Zhang and Martinez, 2004). Recognition techniques based on local regions have achieved high accuracy rates. Though the face images are affected due to variations such as non uniform illumination, expressions and partial occlusions, facial variations are conûned mostly to local regions [14]. 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 neighbouring 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 implemented in this paper which considers additional pixel dependencies across various sub-regions. This helps in providing additional information that could help in improving the classiûcation accuracy. Also, linear subspace approaches such as PCA will not be able to capture the relationship among more than two variables. They cannot depict the variations caused by illuminations, expressions, etc., properly. In order to capture the relationships among more than two pixels, the data is projected into nonlinear higher dimensional spaces using the kernel method. This enables to capture the nonlinear relationships among the pixels within the modules.

FACE RECOGNITION

In this Face Recognition technique, First phase congruency is applied on visible images. Implementing the localization and creating modular regions on the phase congruency plot. Obtain the weights for each individual module using the vectorized modules and the kernel matrix. Classify each module by using a minimum distance classifier on the generated weights from the training and the testing phase. Face recognition technique, is termed as Neighbourhood Defined Modular Spaces Phase Congruency kernel Principal Component Analysis (NMPKPCA).

The training phase of the proposed face recognition technique is illustrated in Figure 1.

Figure 1: Flowchart of Face Recognition



A. Phase Congruency

Phase congruency provides a measure that is independent of the overall magnitude of the signal making it invariant to variations in image illumination and/or contrast. The phase congruency technique used in this research is based on the one developed by Kovesi (Kovesi, 2002). This is in turn based on the local energy model developed in (Morrone and Owens, 1987) to calculate the phase congruency. It has been explained that the point of strong phase congruency should relate to a maximum in the energy of the wave form. It is proposed in [15] that energy is equal to phase congruency scaled by the sum of the Fourier amplitudes as in (1)

$$E(x) = PC(x)\Sigma_n An \quad ...(1)$$

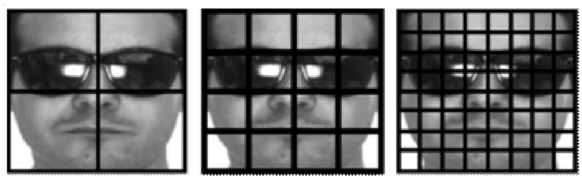
This measure of phase congruency stated as the ratio of E(x) to the overall path length taken by the local Fourier components in reaching the end point, makes the phase congruency independent of the overall magnitude of the signal. This provides invariance to variations in image illumination and contrast. In order to calculate the local frequency and phase information in the signal, logarithmic Gabor functions are used. If all the Fourier amplitudes at are very small then the problem of phase congruency become ill conditioned. To overcome the problem a small positive constant is added to the denominator. The final phase congruency equation is given by

$$PC(x) = \frac{E(x)}{\in + \Sigma_n An} \quad ...(2)$$

B. Local Regions and Variations

Local facial variations caused by expressions, make up, etc., can be dealt more effectively by considering a region based feature extraction approach. This can improve the classiûcation ability (Ben Abdelkader and Griffin, 2005). Dividing the images into sufficiently smaller modules would help in localizing the facial variations. Figure 2 illustrates the concept of localization of variations and pixel dependencies. It can be seen that variations in this image are caused due to face accessories (sunglasses).The localization of those variations gets better with smaller modules. But in doing so, a large amount of dependencies among various neighbouring pixels are ignored. This can be countered by making the modules larger, but this will result in improper localization of the facial variations. In order to deal with this problem, a module creation strategy is implemented in this paper.

Figure 2: Illustration of Concept of Localization of Variations and Pixel Dependencies



Neighbourhood Defined Modular Spaces

Smaller sub-regions from a predeûned neighbourhood within the phase congruency images of the training samples are merged to obtain a large set of modules. As variations in face images are conûned to local regions, it is possible to consider additional pixel dependencies across various sub-regions and also to localize the variations by merging the modules. This helps in improving the classiûcation accuracy.

General steps for the proposed modularization technique for an image of size dimensions are as follows.

1. Each image is divided into non overlapping

regions of size to get number of neighbourhoods (large modules).

2. Each neighbourhood of size is then divided into modules of size, where is the number of small modules within a neighbourhood..
3. P modules can then be created by merging ixj number of small modules in a neighbourhood according to the relation, P = (ixj)!/(k!(ixj – k)! where k is the number of small modules to be merged.

C. Kernel Principal Component Analysis

PCA encodes the pattern information based on second order dependencies, i.e., pixel wise covariance among the pixels, and are insensitive to the dependencies of multiple (more than two) pixels in the patterns. Since the eigenvectors in PCA are the orthonormal bases, the principal components are uncorrelated. In other words, the coefficients for one of the axes cannot be linearly represented from the coefficients of the other axes. Higher order dependencies in an image include nonlinear relations among the pixel intensity values, such as the relation- ships among three or more pixels in an edge or a curve, which can capture important information for recognition. Explicitly mapping the vectors in input space into higher dimensional space is computationally intensive. Using the kernel trick one can compute the higher order statistics using only dot products of the input patterns. Kernel PCA has been applied to face recognition applications and is observed to be able to extract nonlinear features.

The steps involved in the classiûcation of a test image are as follows.

1) Extract the phase congruency features of the test image.
2) Create the modular regions.
3) Obtain the weights for each individual module using the vectorized modules and the kernel matrix.
4) Classify each module by using a minimum distance classiûer on the generated weights from the training and the testing phase.

Gaussian radial basis function (GRBF) kernel and a polynomial kernel function are used in this paper. It is inferred from the literature that the GRBF kernel provided better results in several classiûcation problems [8]. Equation (3) represents the Gaussian RBF kernel and (4) represents the polynomial kernel function

$$K(x,y)= \exp(-(|x-y|^2)/\sigma) \qquad ...(3)$$

$$K(x,y)=(x.y+1)^d \qquad ...(4)$$

RESULTS AND DISCUSSION

As algorithm written in Matlab code, separate functions are written for phase congruency, neighbourhood modular spaces, kernel principal component analysis and for classifying distance measure. After execution of the program which generation of the gui window. Here the consists of the three image displaying, one for the input image ,one for the phase congruency,& for the recognition image.

For a test image, The NMPKPCA process is done and comparison of the features with the database image will be done. If the features are matched then it is said to be called as recognized-NMPKPCA process as illustrated in Figure 3.

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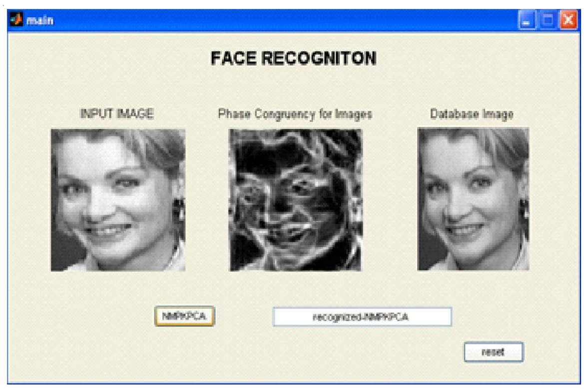
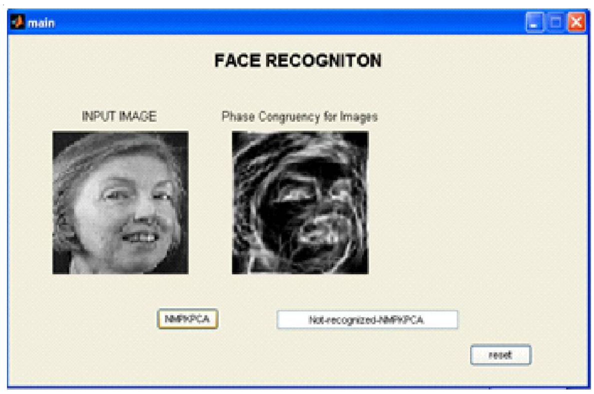
Figure 3: Illustration of Recognized NMPKPCA Process



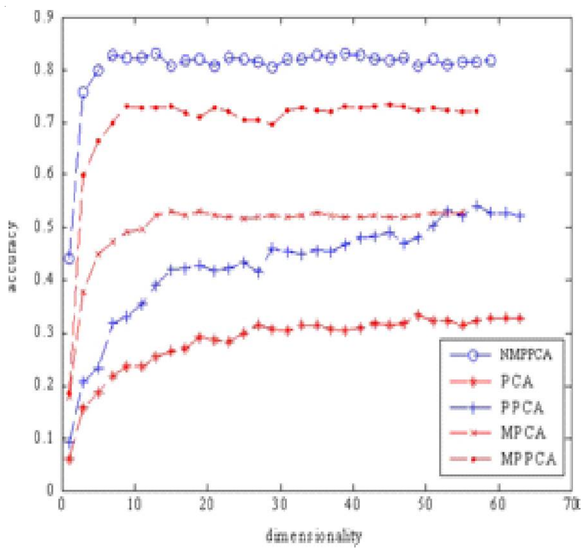
are not matched then it is said to be called as Not-recognized-NMPKPCA process as illustrated in Figure 4.

Figure 4: Illustration of Not-recognized NMPKPCA Process



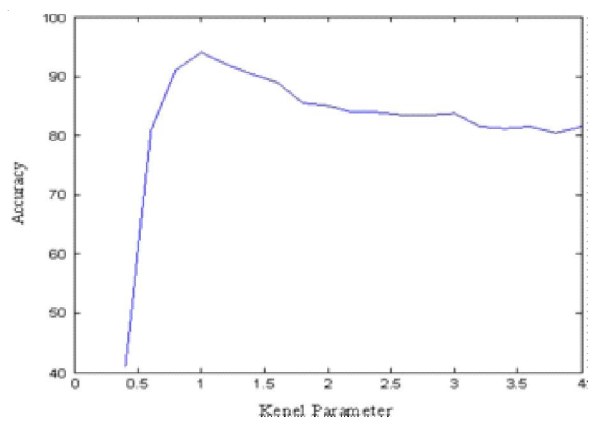
From these results ,we can observe that the recognition is clear with the good expressions. In which the recognition of the images is done very effectively, where the accuracy with the original image is 98%. When compare with other face recognition techniques like PCA, MPCA,PPCA, & NMPCA. The graph in Fig. 5 illustrates the relationship between percentage of accuracy and the dimensionality of the subspace for various methods namely principal component analysis onholistic faces (PCA), modular PCA (MPCA), principal component analysis on phase congruency features (PPCA), modular subspace approach on phase congruency features (MPPCA)and the method of neighbourhood defined module selection on phase congruency features in a PCA domain (NMPPCA). It shows that the use of phase congruency features improves the face recognition accuracy significantly. Also, modular subspaces improve the recognition for both intensity and phase congruency features. The recognition accuracy of NMPPCA is 10% higher than MPPCA.

Figure 5: Accuracies of Various Methods With Respect to Increase in Dimensionality of the Subspace



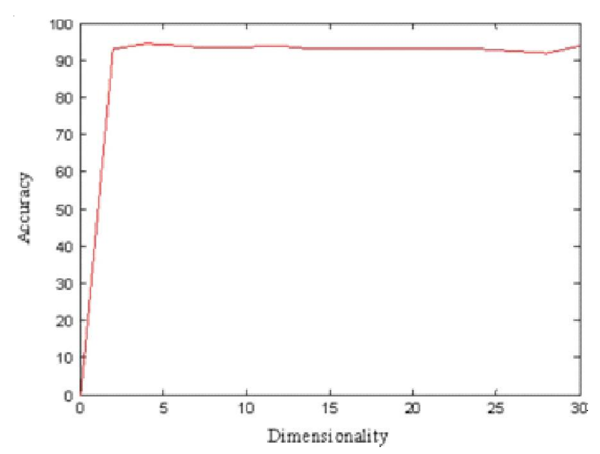
The kernel parameter for the Gaussian RBF kernel is the standard deviation. Fig. 6 shows a graph between the accuracy obtained versus the kernel parameter. Figure 7 shows that the accuracy is highest when the kernel parameter is "1." In the optimum dimensionality is calculated experimentally. Figure 7 shows the graph of accuracy versus varying dimensionality.

Figure 6: Parameter "σ" of the RBF Kernel Vs. Accuracy



A similar procedure of optimizing the kernel parameters is carried out for the polynomial kernel. It is observed that the results obtained for the polynomial kernel, with parameter "d" gave a maximum accuracy.

Figure 7: Accuracy Versus Dimensionality For A Constant Kernel Parameter of "1" for NMPKPCA Technique



CONCLUSION

This paper presented a face recognition technique using visual images. The feature selection strategy is robust to the variations that occur in the face images captured. The novel modular kernel Eigen spaces approach has been able to provide high recognition accuracy in images affected due to partial occlusions, expressions and nonlinear lighting variations. Experimental results presented show significant improvement in there cognition accuracy of visual images.

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