A Study to Develop Human Face Recognition using PCA, Neural Networks and Wavelet

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***Abstract*-A method to improve the precision of the face recognition with the help of an integrating of WT, PCA and neural networks has been presented in this paper. The three main critical issues for face recognition are- preprocessing, feature extraction and classifying rules. A hybrid approach for employing the three issues has been presented in this paper. A combination of wavelet transform (WT) and PCA has been used for preprocessing and feature extraction. Neural Network is discussed for achieving a fast decision in the presenceofvarietyoffacialexpressions,intheclassificationstage.Overall,improvisationsintheproposed method's accuracy isdone.**

INTRODUCTION

Theauthenticationofusershavebeenincreasinginthepastfewyears,becausetherequirementofsecurity isomnipresent.originally,identificationcardsandpasswordswerepopularforprovingauthenticity,though security through these methods is not very reliable. The latest interest of the researchers are authentication technologies based on biology, such as the ones that use iris, fingerprint, face, print of the palm and voice. Face recognition has gained popularity, largely because the process of authentication is done in a hands free way, without interrupting the activity of the user in any way. also, it is economic due to the low cost of the cameras and computer. Psycho-physicists and neuroscientist have focused on issues like face uniqueness, organization of face memory and the perception of faces by infants in the past 20 years. At the same time, engineers have studied, developed and designed algorithms of face recognition in the last 20 years. This paper focusses on the work of the engineers. Content based approach and face based approach are the two approached of face recognition system done by the computers.

There lation ship between the face boundary and facial eatures like nose, eyes, mouth are used in the content based approach. A huge classification error can be committed in the process of derivation, since all the human faces have features that are similar.

Inthefacebasedapproach,thefaceiscapturedasawholeandistreatedasa2Dpattern.Thefaceismatched with the statistical regularities. Principal Component Analysis (PCA) is a face based approach, which has been proven to beeffective.

Karhunen- Loeve (KL) transform was proposed the representation of human faces by Sirovich and Kirby. The faces are represented with the help of eigenfaces, which are the linear combinations of weighed eigenvector, in this method. However, a system of face recognition that makes use of the PCA has been developed by Turk and Pentland. But, this method is not free from limitations. The two limitations of this methodsarelargeloadofcomputationandpoor powerofdiscrimination.Themeasuredsimilaritybetween 2 pictures of the same individual by using the PCA method is high. However, the measured similarity of 2 pictures of different people is also high. Therefore, the discrimination power of this PCA method is very poor.

This drawback of PCA was improved by addition of Linear Discriminant Analysis (LDA) by Swets and Weng. A different method for selection of eigenfaces was suggested by O'Toole et al. they stated that the eigenvectors which have large eigenvalues is not the best method to differentiate face image. It was also presented by them that the representations of low dimension are efficient in identification of physical features of the face, like race and gender even though they might not be the best way for the recognition of human faces.

HeavyloadofcomputationintheprocessoffindingeigenvectorsisanotherprobleminPCAbasedmethod is the h. The typical value of computational complexity of $O(d^2)$ is 128x128, where d= number of pixels. The cost of computation is beyond many existing computer's power. However, Matrix Theory tells us that if the number of training images (N) is smaller than the value of d, the complexity of computation will be decreased to $O(N^2)$. Then also if N will increase the load of the computation is increased in cubic order. A newapproachintheapplicationofPCAinthelightofthealreadyexistingPCAapproachhasbeenproposed here. It is proposed that in this method, the image is decayed into many sub bands using the wavelet transform with many frequencycomponents.

Theresultshaveshownthatthe3 levelwavelethasperformedwellinfacerecognition.Themethodwhich hasbeenproposedinthispaperdoesn'tworkontheimageresolutionof128x128,butonalowerresolution of 16x16. Hence, the computational complexity is reduced significantly for many applications, where the training images are more than 16x16. increASed accuracy in the recognition and better discrimination power was observed when PCA was applied on wavelet transform (WT) than when PCA was applied on the entire of the original image.

REVIEW OF PCA

Some major details of PCA are as follows:

Let $X = \{X_{n,} n = 1,..., N\} \in R$ be an ensemble of vectors. When dxd is the product of width and height of the image, the row concatenation of the data of the image is form in the applications of imaging.

$1\ ^{N}$

Let be the average vector in the ensemble $E(X) =X$ N n=1fter subtracting the average from each elementof X,

ensemble of vectors, $X = \{X_{n}, n = 1,..., N\}$ with $X_n = X_n - E(X)$ is received ·

covariance matrix M for the ensemble X is defined by $M = \text{cov}(X) = E(X \otimes X)$, Where M is $d^2 xd^2$ matrix, with elements.

It is a well-known fact of the matrix theory that matrix M is always positive and will only have eigenvaluesthatarenon-negative.ThematrixM oftheeigenvectorsformabasisforRdxd.Thisbasis is called K-L basis.

The eigenvectors in K are arranged in a descending order of eigenvalues in many applications. In order to compute the dxd eigenvalue from M, 2xd2 matrix has to be solved. In most chances, d=128, hence 16x16 matrix is solved for calculating the eigenvectors and eigenvalues.

Computer system’s requirement for the memory and computation are very high. Matrix theory states that ifN<dxd,thatisN,whichisthenumberoftrainingimage,issmallerthanM,thecomputationalcomplexity decreases to O(N). Therefore, the implementation of PCA in characterizing the faces has become flexible. The number of training images in most researches is around 200. But the M rises when the total number of training images in huge, such as2000.

An image’s Wavelet decomposition

In last 10 years, WT has become a useful tool in the analysis of the image. In this paper, WT has been chosen as the option of choice for image decomposition because-

- The resolution of the sub images are decreased when an image is decomposed by using the WT method. so, the computational complexity also decreases because it operates on an image which has alow resolution. It was observed by Harmon that a resolution of 16x16 is enough for human face recognition. When compared to the original image having a resolution 128x128, it leads to a reduction off the sub image by 64 times, thus implying a reduction on the computational load of 64 times.
- TheimagesaredecomposedintosubbandswhichcorrespondtovariousfrequencyrangesundertheWTmethod. The computational overhead is minimized as the sub bands readily meet the input requirement in the system proposed in this paper.
- While the Fourier decomposition support only the global information in the frequency domain, the WTmethodofdecompositionofimagesprovideslocalinformationindomainsfor bothfrequencyandspace.

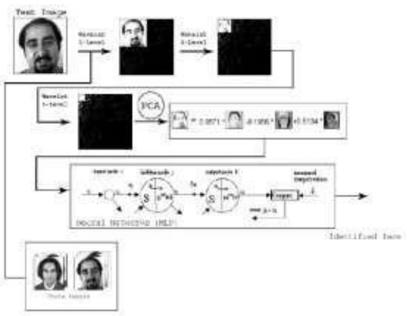
a modified

In this paper, we applied two well-known mother wavelet Daubechies and Haar. We proposed method that uses by coefficients:

h0 = 0.48296291314453 h1 =0.83651630373781
h2 =0.22414386804201
h3 =0.12940952255126
For daubechies mother wavelet and coefficients:
h0 =0.5,h1 =0.5

PROPOSED METHOD

In order to overcome the limitations of the PCA method, this wavelet based PCA method has been developed. also, utilizationof neural networks have been used for classifying faces. A multilayer architecture was adopted,which is fed by the vectors formed by combining wavelet and PCA and decreased inputunits.Usingaparticularfrequencybandofanimageofthefaceforsolvingthefirstproblem of PCA has beenproposed.



Using a reduced resolution image for dealing with the second limitation of the PCA has been proposed. The proposed system has two stages. one, “training step” in which extractions of features, reduction of dimensions and adjustment of weight of MLP neural networks is done. Second, “recognition step” for identifying the unknown images of faces.

In the “training stage”, “feature extraction of reference images” and “adjusting the neural network parameters” is included. In interested domain, the "representational basis" of the images is identified in featureextraction.Then,inputimageistranslatedinaccordancewiththerepresentationalbasis(whichhave been identified in the training stage) in the "recognitionstage".

The 3 important steps in the "training stage" are-

1. For decomposing the reference images, WT is applied. Then, by the decomposition of the wavelet in three levels, sub images of 16x16 pixels which have been obtained, areselected.
2. For obtaining a set of representational basis, by selecting d' eigenvectors which correspond to large eigenvalues and sub space projection, PCA is applied on the subimages.
3. The obtained features of the reference images in the precious step are then used for training neural networks with the help of propagation algorithm. The processing carried out in both the training and recognition stage is similar, the only difference being in the recognition stage, the input unknown images are matched with reference images in the recognition stage. WT and PCA are used for transforming the unknown face images intro the representational basis when an unknown face is presented in the recognitionstage.

EXPERIMENTAL RESULT

The database of face image of Yale university and face database of ORL is used for evaluating the the method that has been proposed in this paper.

All the images in the database of Yale university have a 160x121 resolution. But the WT can't be applied as the images' dimension are not the power of 2. The images were then cropped to 91x91, and hen resized in 128x128. A third level of WT decomposition was use for changing the resolution of images.

Table 1 and table 2 show the results of the proposed algorithm on the database of Yale university and database of ORL, and have used the hair mother wavelet. The results of the proposed algorithm in the database of Yale and ORL which have used Daubechies mother wavelet has been shown in table 3 and 4. The performance in recognition on the test image of the Yale and ORL database which have used various components have been shown in table 5 and 6.

TABLE 1. Algorithm applied on Yale database and haarmotherwavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	81.78%	82.2%

TABLE 2. Algorithm applied on ORL database and haarmotherwavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	90%	91.80%

TABLE 3. Algorithm applied on ORL database and Daubechies motherwavelet.

	PCA on image	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	90%	97.68%

TABLE 4. Algorithm applied on Yale database and Daubechiesmotherwavelet.

	P C A	PCA on LL band of three level wavelet
Size of image	128*128	16*16
Recognition rate	81.78 %	90.35%

TABLE 5. Recognition performance on testimagesof Yale database using the number ofprincipal components.

Number	ANN structure	Recog.	Average
1-15	15:25:15	88.37%	86.56%
1-25	25:30:15	90.35%	89.23%
1-35	35:30:15	89.78%	87.24%
1-45	45:25:15	88.92%	87.68%
1-60	60:35:15	83.78%	88.23%
1-80	80:40:15	85.56%	
1-105	105:45:15	84.76%	83.67%

TABLE 6. Recognition performance on test images of ORL database using the number of principal components.

Number of P.C	ANN structure	Recog. rate (15 attempts)	Average of recognition
1-25	25:40:40	95.37%	94.14%
1-30	30:80:40	94.47%	93.15%
1-35	35:80:40	96.81%	95.45%
1-40	40:40:40	97.68%	96.56%
1-50	50:40:40	96.56%	95.24%
1-100	100:60:40	92.22%	91.72%

TABLE 7. Recognition performance on test images of Yale database using MLP Neural networks by 25of principal components.

Number of P.C	ANN structure	Recog.rate(10 attempts)	Average of recognition
1-25	25:15:15	89.69%	87.56%
1-25	25:20:15	90.06%	89.45%
1-25	25:25:15	90.10%	89.25%
1-25	25:30:15	90.35%	89.23%
1-25	25:40:15	90.05%	87.45%
1-25	25:50:15	90.%	88.34%
1-25	25:60:15	89.86%	87.24%

TABLE 8. Recognition performance on test images of ORL database using MLP Neural networks by 40 of principal components.

Numberof P.C	ANN structure	Recog. Rate (15attempts)	Averageof recognition
1-40	40:10:40	89.67%	87.64%
1-40	40:20:40	91.34%	90.78%
1-40	40:30:40	96.99%	94.67%
1-40	40:40:40	97.68%	96.58%
1-40	40:50:40	96.89%	95.24%
1-40	40:60:40	96.57%	95.67%
1-40	40:70:40	95.98%	94.67%

CONCLUSION

A hybrid approach for face recognition has been presented in this paper, by taking care of three issues. For stagesoffeaturerecognitionandpreprocessing, WTandPCAhavebeenappliedina combinedform.And MLP has been explored for quick decision making when there is a wide variety of facial variations in the classification stage. It can be concluded based on the experiments done on Yale university and ORL databasethatacombinationofWT,PCAandMLPyieldsmost favorableperformance,becauseitexhibits the lowest redundant rate, lowest training time and highest rates ofrecognition.

The proposed method also exhibits the a low load of computation in both the stages- training and recognition.

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