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Utilizing DCT and PCA Methods for Facial Recognition

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ABSTRACT

A recognition system for faces, a complex multidimensional structure, necessitates effective computing techniques. This study employs Principal Component Analysis (PCA) and Discrete Cosine Transform (DCT) for face recognition. The process involves projecting face images onto a face space that captures optimal variations among known face images, defined by eigenfaces as eigenvectors of the face set. In the DCT approach, the image undergoes transformation into the frequency domain, enabling feature extraction. Two distinct approaches are employed for feature extraction: the first involves taking the DCT of the entire image, while the second entails dividing the image into sub-images, performing DCT on each, and extracting the feature vector.

Keywords—Face recognition, Principal component analysis (PCA), Artificial Neural network (ANN), Eigenvector, and Eigenfaces

Introduction

1.1 Biometrics

Biometrics plays a crucial role in authenticating individuals by confirming or establishing the identity of a person seeking access to a network resource. The authentication process involves verifying or identifying the user based on inherent human traits, such as fingerprints or facial features. By comparing the provided data with existing records, the identity of a specific individual can be confirmed. Various types of biometric systems, including fingerprint recognition, face detection and recognition, and iris recognition, utilize these distinctive human traits for identification purposes in surveillance systems and criminal identification. The advantages of employing such traits lie in their uniqueness and the fact that they cannot be easily forgotten or lost, contributing to their widespread use.

1.2 Face Recognition

Facial recognition involves addressing the complexity of the face as a multidimensional structure, requiring advanced computing techniques for accurate identification. The face, being a primary focal point in social interactions, plays a crucial role in individual identity. Throughout our lives, we develop the ability to recognize numerous faces, even with potential variations due to factors such as aging, facial hair, glasses, or changes in hairstyles.

Biometric systems, where fundamental human traits are matched with existing data, form an integral part of face recognition. Algorithms efficiently extract facial features, and adjustments are made to enhance existing models. Computers equipped with face detection and recognition capabilities find applications in criminal identification, security systems, and identity verification. These technologies are increasingly employed on websites hosting images and social networking platforms.

Facial recognition and detection, rooted in computer science, involve the extraction and processing of features from a face. These processed features are then compared with similar data in the database. Recognized faces are identified, while unknown faces may prompt the system to display similar faces from the database. Surveillance systems utilize this process, storing unknown faces for subsequent recognition if they appear more than once. These steps are particularly valuable in criminal identification.

In a broader context, facial recognition techniques can be categorized into two groups: appearance-based, which employs holistic texture features and can be applied to either the entire face or specific regions, and feature-based, which relies on geometric facial features (mouth, eyes, brows, cheeks, etc.) and their geometric relationships.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was introduced by Karl Pearson in 1901 as a statistical technique based on linear transformation. Its primary purpose is to reduce the dimensionality of data and mitigate correlations between variables. PCA serves as a method for identifying patterns within data, expressing the information in a manner that emphasizes both similarities and differences. Given the challenge of identifying patterns in high-dimensional data, especially when graphical representation is impractical, PCA emerges as a robust tool for multi-dimensional tasks like face detection.

The core objective of PCA is to transform the data space from a large dimension to a more compact intrinsic dimension represented by a feature vector (independent variable). This transformation allows for a more cost-effective description of the data. The first principal component is a linear combination of the original dimensions, capturing the direction in which the variance is maximized. Subsequently, each successive principal component is a linear combination that maximizes variance while remaining orthogonal to the preceding components.

In essence, PCA provides an effective means of reducing the complexity of data by extracting essential features and highlighting the most significant variations, making it particularly valuable in applications such as face detection.

Discrete Cosine Transform (DCT)

A transform is a mathematical operation applied to a signal during processing, converting it into a different domain. The transformed signal can then be reverted to its original domain using an inverse transform. This process provides a set of coefficients from which the original samples of the signal can be reconstructed. Certain mathematical transforms have the capability to produce decorrelated coefficients, concentrating most of the signal energy in a reduced number of coefficients.

The Discrete Cosine Transform (DCT) is one such transform that aims to decorrelate image data, similar to other transforms. Through decorrelation, each transform coefficient becomes independently encodable without sacrificing compression efficiency. The DCT represents a finite sequence of data points as a sum of cosine functions oscillating at different frequencies. The resulting DCT coefficients capture various frequency components present in the data. The initial coefficient corresponds to the signal's lowest frequency (DC component) and typically contains the majority of relevant information from the original signal. Subsequent coefficients, positioned towards the end, pertain to higher frequencies, representing finer details. The remaining coefficients convey distinct information levels of the original signal.

PCA IN DCT DOMAIN

In the pattern recognition letter authored by Weilong Chen, Meng Joo Er, and Shiqian Wu, it has been demonstrated that applying Principal Component Analysis (PCA) directly to the coefficients of the Discrete Cosine Transform (DCT) is feasible. When PCA is employed on an orthogonally transformed version of the original data, the subspace projection obtained is equivalent to the results obtained by applying PCA directly to the original data. Both DCT and Block-DCT, where images are divided into small blocks and the DCT is applied to each subimage, constitute orthogonal transforms. Consequently, PCA can be applied to these transforms without experiencing any reduction in performance.

Basic Algorithm For Face Recognition

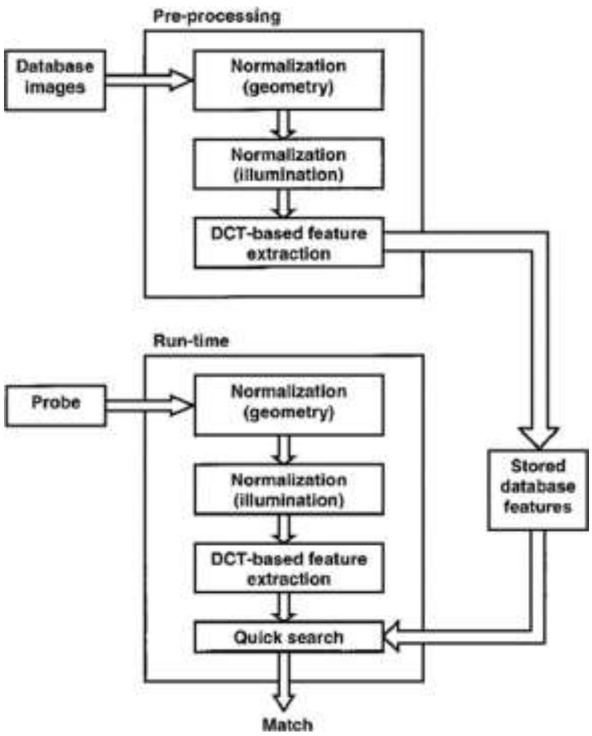


Fig 3.1 Basic algorithm for face recognition

Implementation

PCA: Matlab 2011a is used for coding. The face images are cropped and converted to grey scale images as grey scale images are easier for applying computational techniques in image processing. The database is used FACES94 database and AT&T (the ORL database).

Few of the images from the database

We have conducted five sets of experiments by considering 5 , 10 , 20 , 40 and 60 each time. For each person we have taken a few no photos with different orientations and expressions.

In each experiment we have used the algorithm discussed in the previous chapter and have found out the principal components. Then by taking certain no of principal components at a time we have formed the face space.

Shows the image of 10 person in different pose

DCT:We have used Matlab 2011a is used for implementation. We use the same data base as the above case. The face images are cropped and changed grey level. Next we convert the image to DCT domain for feature extraction. The feature vector is dimensionally much less as compared to the original image but contains the required information for recognition.

The DCT of the image has the same size as the original image. But the coefficients with large magnitude are mainly located in the upper left corner of the DCT matrix.

Low frequency coefficients are related to illumination variation and smooth regions (like forehead cheek etc.) of the face. High frequency coefficients represent noise and detailed information about the edijes in the image. The mid frequency region coefficients represent the general structure of the face in the image.

Hence we can't ignore all the low frequency components for achieving illumination invariance and also we can't truncate all the high frequency components for removing noise as they are responsible for edges and finer details.

Sample Image

DCT of image

Histogram equalized version of the DCT

Result

Result and Analysis

Threshold value of the test face image to Eigen face space which is Euclidean distance is taken as 7.6 which classify the face as known or unknown.

Comparison between different experimental Results of PCA approach

No. of Person	**No. of Photos Per Person**	**Total no. of Test faces**	**Total no.of Eigenface Taken**	**Success Rate PCA Approach**
5	4	20	5	71%
5	4	20	10	76%
5	4	20	15	84%
5	4	20	20	86%
10	4	40	5	69%
10	4	40	10	72%
10	4	40	15	82%
10	4	40	20	85%

Comparison between different experimental Results of DCT approach

No. of Person	**No. of Photos Per Person**	**Total no. of Test faces**	**Total no. of Eigenface Taken**	**Success Rate**	
				DCT	**BLOCK-DCT**
5	8	40	10	80%	82%
5	8	40	15	85%	85%

5	8	40	20	88%	90%
10	8	80	10	76%	78%
10	8	80	15	82%	83%
10	8	80	20	85%	86%
20	8	160	10	72%	74%
20	8	160	15	75%	76%
20	8	160	20	80%	80%

Four different images for each mentioned condition were taken to test for five and ten different people. Light intensity is tried to keep low. Size variation of a test image is not altered to much extent. We can observe that normal expressions are recognized as face efficiently because facial features are not changed much in that case and in other cases where facial features are changed efficiency is reduced in recognition.similarly the results shows poor performances for lesser eigenfaces.

Average Success Rate

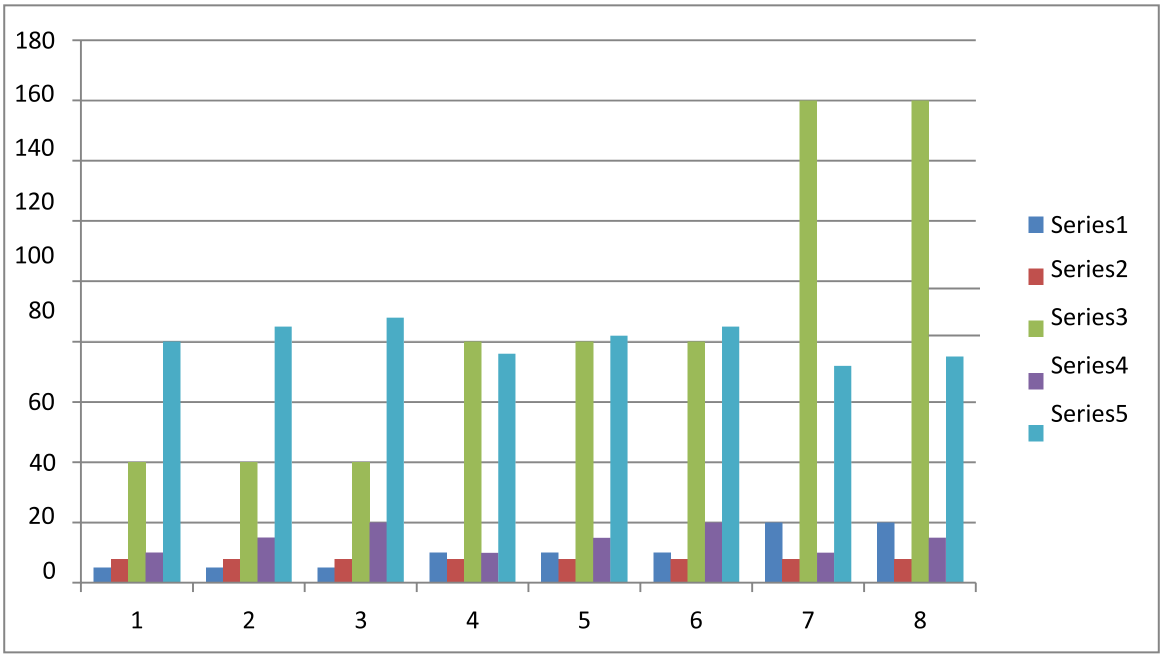
(71+ 76+ 84+ 86+ 69 + 72+82+85)/8 = 78.125% for PCA

(80+85+88+76+82+85+72+75+80)/9 = 80.333% for DCT

(82+85+90+78+83+86+74+76+80)/9 = 81.556% for Block-DCT

However, this efficiency cannot be generalized as it is performed on less number of test of images and conditions under which tested may be changed on other time.

Graph of the Result



Series 1: No. of Person Series 2 No. of Photos Per Person Series 3: Total no. of Test faces Series 4: Total no. of Eigenface Taken Series 5: Success Rate

Conclusion

In this thesis we implemented the face recognition system using Principal Component Analysis and DCT based approach. The system successfully recognized the human faces and worked better in different conditions of face orientation upto a tolerable limit. But in PCA, it suffers from Background (deemphasize the outside of the face, e.g., by multiplying the input image by a 2D Gaussian window centered on the face), Lighting conditions (performance degrades with light changes),Scale (performance decreases quickly with changes to the head size), Orientation (performance decreases but not as fast as with scale changes).similarly

In block DCT based approach our the results are quite satisfactory. But it suffers from its problem that all images should align themselves in the centre position minimizing the skewness of the image to lower level.

REFERENCES

[1] Manzoor .A. Lone , S . M .Zakariya," Automatic Face Recognition System By Combining Four Individual Algorithms " , International Conference on Compufation Intelligence and Communication Systems , 2011 . 44 .

[2] M . Sharif , M . A . Ali , M . Raza , S . Mohsin , " Face Recognition usig Edge Information and DCT " , Sindh University Research Journal , 2011 , pp . 209-214 .

[3] KresimirDelac , MislavGrgic , Sonja Grgic " Independent Comparative Study of PCA and LDA on the FERET Dataset " University of Zagreb , FER , 2006 .

[4] Sung . Kwunoh , Sung . Hoonyoo , WitoldPednycz , " Design of Face Recognition Algorithm using PCA – LDA Combined for Hybrid Data Preprocessing and Polynomial based RBF neural networks Design and its application " , Expert System with applications 40 (2013) 1451 – 1466 .

[5] Iftikhar Ahmad ,"Enhancing MLP Performance in Intrusion Detection Using Optimal Feature Subset Selection Based On Genetic Principle Component ",Applied Mathematics & Information Sciences,2014,pp.639-649

[6] UrvashiBakshi , RohitSinghal " A new Approach of Face Recognition using DCT, PCA, and Neural Network in Mat lab" , International Journal of Emerging Trends &Technology in Computer,2014,pp.2278-6856.

[7] Kiran D. Kadam,"Face Recognition using Principal Component Analysis with DCT " ,International Journal of Engineering Research and General Science,2014,pp.2091-2730.

[8] DebaraRana , Sunita , Bhawna, SujataMinz, N.Prasanna, TapasmitaSahu,"Comparative Analysis of Face Recognition using DCT ,DWT and PCA for Rotated Faces", International Journal of Scientific Research Engineering &Technology , 2014,pp2278-2282.

[9] Changjan Zhou, LanWang,Qiang Zhang , Xiaopeng Wei, "Face Recognition Based on PCA Image Reconstruction and LDA ", Optik,2013, pp.5599-5603.

[10] Akrouf Samir, Sehili Med Amine , ChakhchoukhAbdesslem , MostefaiMessaoud ,"Face Recognition using PCA and DCT" ,Fifth International Conference on MEMS NANO and Smart System, 2009.

[11] TheDatabaseAT&Toffaces, http://www.cl.cam.ac.uk./research/dtg/attarchive/facedatabase. html.

[12] TheDatabase of FACES94, http://cmp.felk.cvut.ci/space lib/faces/faces94.html.