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Metamorphism using Warping and Vectorization Method for Image:Review

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Abstract:
Face recognition presents a challenging difficultly in the field of image analysis and computer vision, and as such has received a great deal of devotion over the last few years because of its many tenders in various domains. In this paper, an overview of some of the well-known methods. The applications of this technology and some of the difficulties plaguing current systems with regard to this task have also been provided. This paper also mentions some of the most recent algorithms developed for this purpose and attempts to give an idea of the state of the art of face recognition technology.

Keywords: *Face recognition, biometric, algorithms*

INTRODUCTION:

Interest in face recognition is moving toward uncontrolledor moderately controlled environments, in that either theprobe or gallery images or both are assumed to be acquiredunder uncontrolled conditions. Also of interest are morerobust similarity measures or, in general, techniques todetermine whether two facial images correctly match, i.e.,whether they belong to the same person.An important real-life application of interest is automatedsurveillance, where the objective is to recognize and trackpeople who are on a watch list. In this open world applicationthe system is tasked to recognize a small set of people whilerejecting everyone else as being one of the wanted people.Traditionally, algorithms have been developed for closedworld applications. Theassumption is that the probe image and its closest image inthe gallery belong to the same person. The information obtained by this search is then used to dorecognition. Currently, the technology is used by police, forensic scientists, governments, private companies, the military, and casinos. The police use facial recognition for identification of criminals. Companies use it for securing access to restricted areas. Casinos use facial recognition to eliminate
Cheaters and dishonest money counters. Finally, in the United States, nearly half of the states use computerized identity verification, while the National Center for Missing and Exploited Children uses the technique to find missing children on the Internet. In Mexico, a voter database was compiled to prevent
vote fraud. Facial recognition technology can be used in a number of other places, such as airports, government buildings, and ATMs (automatic teller machines), and to secure computers and mobile phones.Computerized facial recognition is based on capturing an image of a face, extracting features, comparing it to images in a database, and identifying matches. As the computer cannot see the same way as a human eye can, it needs to convert images into numbers representing the various features of a face. The sets of numbers representing one face are compared with numbers representing another face.
The excellence of the computer recognition system is hooked onthe quality of the image and mathematical algorithms used to convert a picture into numbers. Important factors for the image excellence are light, background, and position of the head. Pictures can be taken of a still or moving subjects. Still subjects are photographed, for example by the police (mug shots) or by specially placed security cameras (access control). However, the most challenging application is the ability to use images captured by surveillance cameras (shopping malls, train stations, ATMs), or closed-circuit television (CCTV). In many cases the subject in those images is moving fast, and the light and the position of the head is not optimal.
Face Recognition
Challenges

- Physical appearance
- Acquisition geometry
- Imaging conditions
- Compression artifacts

1. **Face Detection**

- Face detection task: to identify and locate human faces in an image regardless of their position, scale, in plane rotation, orientation, pose (out of plane rotation), and illumination.
- The first step for any automatic face recognition system
- Face detection methods:

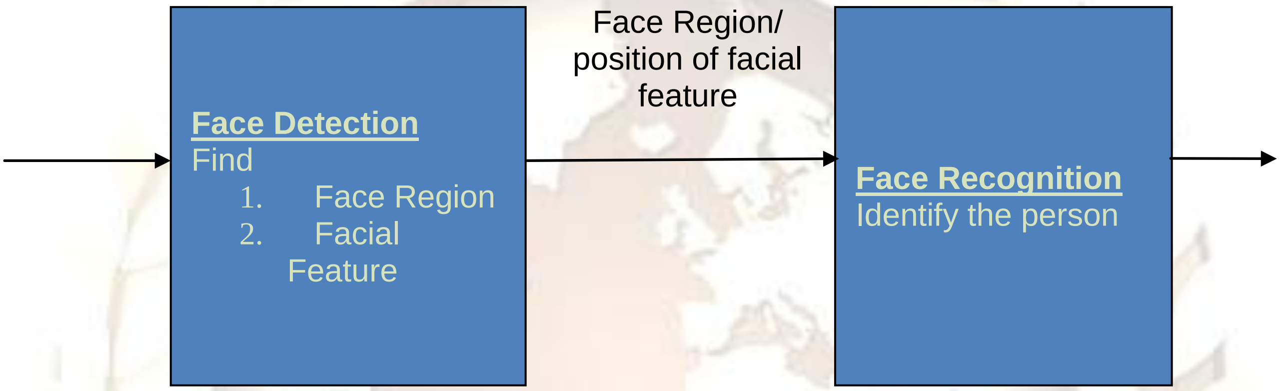
Knowledge-based: Encode human knowledge of what constitutes a typical face (usually, the relationship between facial features)

Feature invariant approaches: Aim to find structural features of a face that exist even when the pose, viewpoint, or lighting conditions vary

Template matching methods: Several standard patterns stored to describe the face as a whole or the facial features separately. The most direct method used for face recognition is the matching between the test images and a set of training images based on measuring the correlation. The similarity is obtained by normalize cross correlation.

Appearance-based methods: The models (or templates) are learned from a set of training images which capture the representative variability of facial appearance

Framework of Face recognition



Face Recognition

In general, face recognition systems proceed by identifying the face in the scene, thus estimating and normalizing for translation, scale, and in-plane rotation. Many approaches to finding faces are based on weak models of the human face that model face shape in terms of facial texture.
Once a prospective face has been localized, the approaches to face recognition then divided into two categories:

- Face appearance
- Face geometry

Face Recognition: Advantages

- Photos of faces are widely used in passports and driver's licenses where the possession authentication protocol is augmented with a photo for manual inspection purposes; there is wide public acceptance for this biometric identifier
- Face recognition systems are the least intrusive from a biometric sampling point of view, requiring no contact, nor even the awareness of the subject
- The biometric works, or at least works in theory, with legacy photograph data-bases, videotape, or other image sources
- Face recognition can, at least in theory, be used for screening of unwanted individuals in a crowd, in real time
- It is a fairly good biometric identifier for small-scale verification applications

Face Recognition: Disadvantages

- A face needs to be well lighted by controlled light sources in automated face
- Authentication systems. This is only a first challenge in a long list of technical challenges that are associated with robust face authentication
- Face currently is a poor biometric for use in a pure identification protocol
- An obvious circumvention method is disguise
- There is some criminal association with face identifiers since this biometric has long been used by law enforcement agencies ('mugshots').

2. Face Recognition Algorithms

3.1 Principal Component Analysis (PCA)

Derived from Karhunen-Loeve's transformation. Given an s-dimensional vector representation of each face in a training set of images, Principal Component Analysis (PCA) tends to find a t-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional (t<<s). If the image elements are considered as random variables, the PCA basis vectors are defined as eigenvectors of the scatter matrix.

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the majorconceivablevariance (that is, accounts for as much of the variability in the data as possible), and each following component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

PCA was invented in 1901 by Karl Pearson [6].Now it is mostly used as a tool in exploratory data analysis and for creatingpredictive models. PCA can be done by eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after mean centering (and normalizing or using Z-scores) the data matrix for each attribute[7]. The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores (the transformed variable values corresponding to a particular data point), and loadings (the weight by which each standardized original variable should be multiplied to get the component score)[7].

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which finestdescribes the variance in the data. If a multivariate dataset is pictured as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

PCA is meticulously related to factor analysis. Factor analysis normally incorporates more domain specific suppositions about the underlying structure and solves eigenvectors of a slightly different matrix.

3.2 Independent Component Analysis (ICA)

Independent Component Analysis (ICA) minimizes both second-order and higher-order dependencies in the input data and attempts to find the basis along which the data (when projected onto them) are - statistically independent. Bartlett et al. provided two architectures of ICA for face recognition task: Architecture I - statistically independent basis images, and Architecture II - factorial code representation. Independent component analysis (ICA) is a computational method from statistics and signal processing which is a special case of blind source separation. ICA seeks to separate a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals. The general framework of ICA was introduced in the early 1980s (Hérault and Ans 1984; Ans, Hérault and Jutten 1985; Hérault, Jutten and Ans 1985), but was most clearly stated by Pierre Comon in 1994 (Comon1994). For a good text, see Hyvärinen, Karhunen and Oja (2001).ICA finds the independent components (aka factors, latent variables or sources) by maximizing the statistical independence of the estimated components.

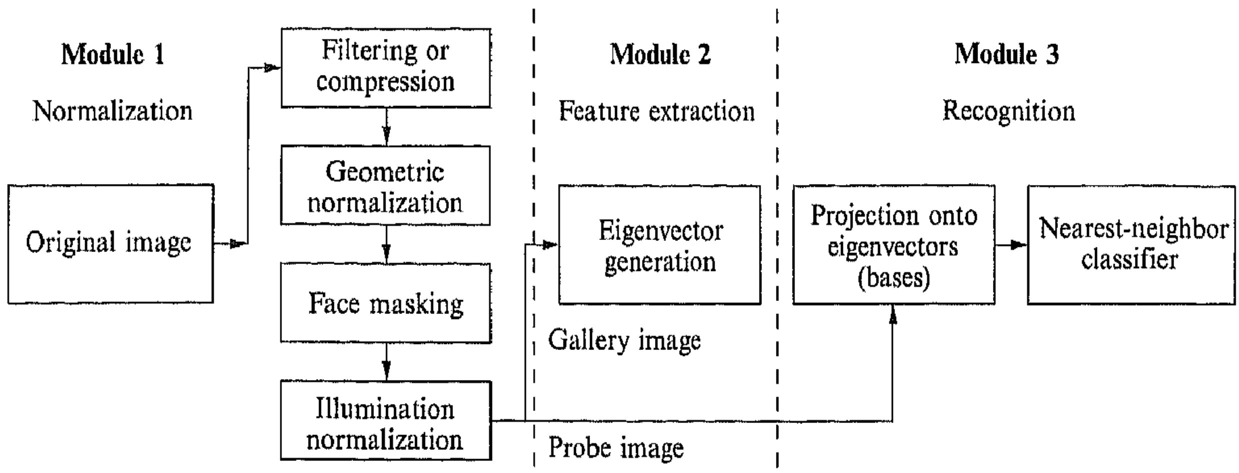


Fig:1 Represents PCA method

We may choose one of many ways to define independence, and this choice governs the form of the ICA algorithms. The two broadest definitions of independence for ICA are

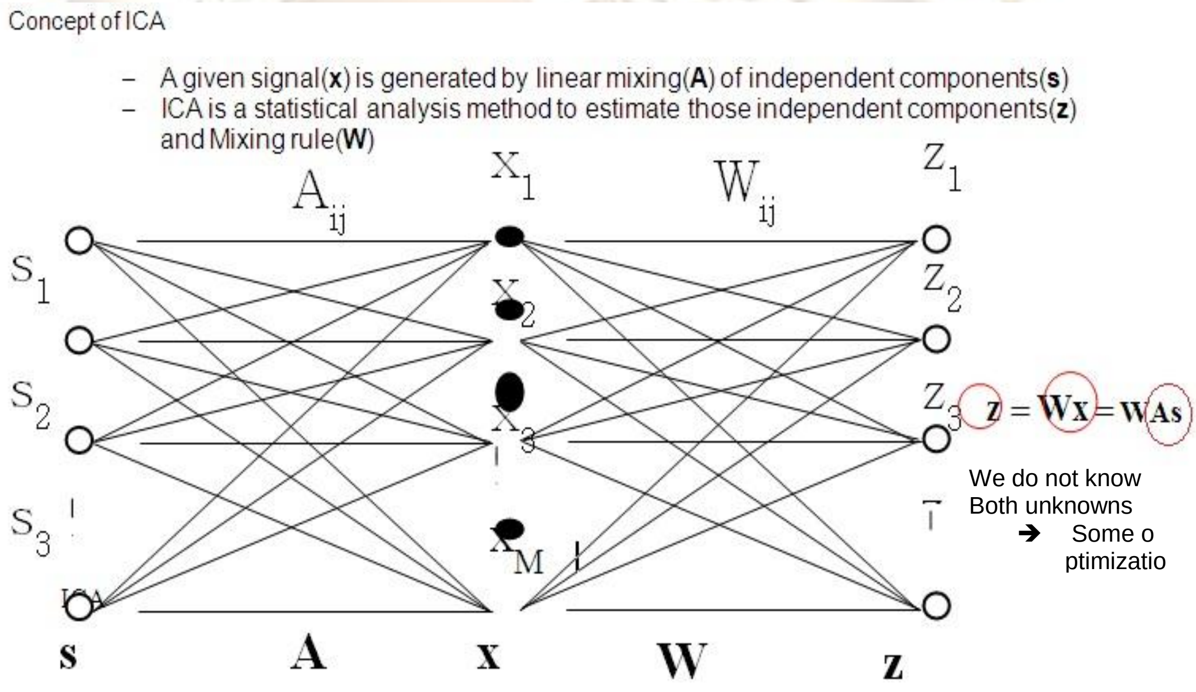
1) Minimization of Mutual Information
2) Maximization of non-Gaussianity
The Minimization-of-Mutual information (MMI) family of ICA algorithms uses measures like Kullback-leiber Divergence and maximum-entropy. The Non-Gaussianity family of ICA algorithms, motivated by the central limit theorem, uses kurtosis and Negentrogy. Typical algorithms for ICA use centering, whitening (usually with the eigenvalue decomposition), and dimensionality reduction as preprocessing steps in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. Whitening and dimension reduction can be achieved with principal component analysis or singular value decomposition [2].

Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals. It is a special case of separation. Whitening ensures that all dimensions are treated equally a priori before the algorithm is run. Algorithms for ICA include infomax, FastICA, and JADE, but there are many others.In general, ICA cannot identify the actual number of source signals, a uniquely correct ordering of the source signals, nor the proper scaling (including sign) of the source signals. ICA is important to blind signal separation and has many practical applications. It is closely related to (or even a special case of) the search for a factorial code of the data, i.e., anew vector-valued representation of each data vector such that it gets uniquely encoded by the resulting code vector (loss-free coding), but the code components are statistically independent.

Comparison of PCA and ICA

PCA
– Focus on uncorrelated and Gaussian components
– Second-order statistics
– Orthogonal transformation

ICA
– Focus on independent and non-Gaussian components
– Higher-order statistics
– Non-orthogonal transformation



ICA

3.3 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) finds the vectors in the underlying space that best categorize among classes. For all samples of all classes thebetween-class scatter matrix SBand the within-class scatter matrix SWare defined.The goal is to maximize SBwhile minimizing SW, in other words, maximize the ratio det|S|/det|SW. This ratio is maximized when the column vectors of the projection matrix are the eigenvectors of (SW^-1 × SB).Linear discriminant analysis (LDA) and the related Fisher's linear discriminantare dimensionality before later classification.LDA is closely linked to ANOVA (analysis of variance) and regressionwhich also attempt to express one dependent variable as a linear combination of other structures or extents[10][3].In the other two methods however, the dependent variable is a numerical quantity, while for LDA it is a categorical variable (i.e. the class label). Logistic regression andprobitregression are more similar to LDA, as they also explain a categorical variable. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.LDA is also closely related to principal component analysis (PCA) and factor analysis in that they both look for linear combinations of variables which best explain the data [3]. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities. Discriminant analysis is also different from factor analysis in that it is not an interdependence technique: a distinction between independent variables and dependent variables (also called criterion variables) must be made.LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis[7][8].

Basic steps of LDA algorithm [3]

LDA uses PCA subspace as input data, *i.e.*, matrix V obtained from PCA. The advantage is cutting the eigenvectors in matrix V that are not important for face recognition (this significantly improves computing performance). LDA considers between and also within class correspondence of data. It means that training images create a class for each subject, *i.e.*, one class = one subject (all his/her training images).

1.Determine LDA subspace (*i.e.* determining the line in Fig. 2) from training data. Calculate the within class scatter matrix

$$S_w \sum_{i=1}^{C} ,s_i = \sum_{x \in x_i} (x-m_i)\,(x-m_i)^T$$

where$m_i$is the mean of the images in the class and C is the number of classes.Calculate the between class scatter matrix

$$\mathbf{2.}\ S_B = \sum_{i=1}^{N} n_i (m_i - m)(m_i - m)^T$$

where$n_i$is the number of images in the class, mi is the mean of the images in the class and m is the mean of all the images.

3.Solve the generalized eigenvalue problem

S*B*V = ^S*W*V

3.4 Hidden Markov Models (HMM)

Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal. HMM consists of two interrelated processes:

(1) An underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and

(2)A set of probability density functions associated with each state.

A Hidden Markov Models (HMM) is a finite state machine which has some fixed number of states. It provides a probabilistic framework for modeling a time series of multivariate observations.

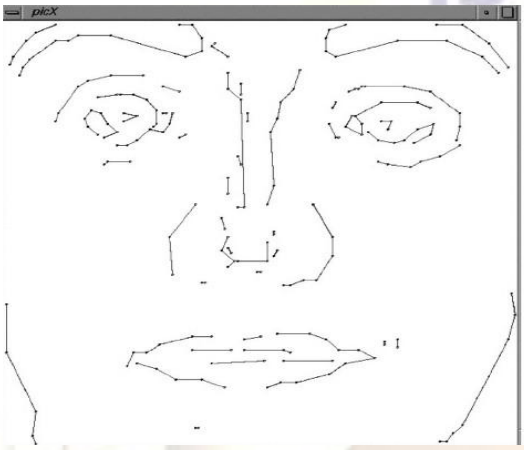
Hidden Markov models were introduced in the beginning of the 1970‟s as a tool in speech recognition. This model based on statistical methods has become progressively popular in the last several years due to its strong mathematical structure and theoretical basis for use in a wide range of applications [1].

A hidden Markov model is a doubly stochastic process, with an underlying stochastic process that is not observable (hence the word hidden), but can be observed through another stochastic process that creates the sequence of observations. The hidden process consists of a set of conditions connected to each other by changes with probabilities, while the observed process consists of a set of outputs or observations, each of which may be emitted by each state according to some probability density function (pdf). Depending on the nature of this pdf, several HMM classes can be distinguished. If the observations are naturally discrete or quantized using vector quantization [11].

3.5Face recognition using line edge map (LEM)

This algorithm describes a new technique based on line edge maps (LEM) to accomplish face recognition. In addition, it proposes a line matching technique to mark this task possible. In opposition with other algorithms, LEM uses physiologic features from human faces to solve the problem; it mainly uses mouth, nose and eyes as the most characteristic ones.

In order to degree the similarity of human faces the face images are initially converted into gray-level pictures. The images are encoded into binary edge maps using Sobel edge detection algorithm. This system is muchrelated to the way human beings perceive other people faces as it was stated in many psychological studies. The main advantage of line edge maps is the low sensitiveness to illumination changes, because it is an intermediate-level image representation derived from low-level edge map representation.[9] The algorithm has another important improvement, it is the low memory requirements because the sensible of data used. In there is an example of a face line edge map; it can be observed that it keeps face features but in a very abridgedlevel [13].



4. Face Recognition Techniques

Taranpreet Singh Ruprahhas presented a face recognition systemusing PCA with neural networks in the context of face verification and face recognition using photometric normalization for association. The experimental results show the N.N. Euclidean distance rules using PCA for overall presentation for verification. However, for recognition, E.D.classifier gives the highest accuracy using the original face image. Thus, applying histogram equalization techniques on the face image do not give much impact to the performance of the system if conducted under controlled environment[17].Byongjoo Ohproposes a face recognition algorithmand presented results of performance test on the ORL database. The PCA algorithm is first tried as a reference performance. Then PCA+MLNN algorithm was proposed and tested in the same environments. The PCA+ MLNN algorithm shows better performance, and resulted in95.29% recognition rate. The introduction of MLNN enhances the classification performance and providesrelatively robust performance for the variation of light. However this result does not guarantee the PCA+ MLNN algorithm is always better than PCA[12].Jan Mazanec and others experiments with FERET database imply that LDA+ldaSoft generally achieves the highest maximum recognition rate. In their experiment they show, LDA alone is not suitable for practical use. At certain parameter settings LDA produced the worst recognition rates from among all experiments. Experiments with their proposed methods PCA+SVM and LDA+SVM produced a better maximum recognition rate than traditional PCA and LDA methods. Combination LDA+SVM produced more consistent results than LDA alone. Altogether they made more than 300 tests and achieved maximum recognition rates near 100% (LDA+SVM once actually 100%)[8].Chengjun Liu and Harry Wechsler address the relative usefulness of the independentcomponent analysis for Face Recognition. The sensitivity analysis suggests that for enhanced performance ICA should be carried out in a compressed and whitened space where most of the characteristic information of the original data is conserved and the small trailing eigenvalues unwanted. The dimensionality of the compressed subspace is decided founded on the eigenvalue spectrum from the training data. In the result their discriminant analysis shows that the ICA criterion, when carried out in the properly compressed and whitened space, performs better than the eigenfaces and Fisherfaces methods for face recognition[4].

5. Conclusions:

Face recognition is a challenging problem in the field ofimage analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted dynamically in this area for the past four agesor so, and though huge progress has been made, encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life.

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