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Face Recognition using ICA for Biometric Security System

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Abstract – **An amount of current face recognition procedures use face representations originate by unsupervised statistical approaches. Typically these approaches find a set of basis images and characterize faces as a linear combination of those images. Principal component analysis (PCA) is a prevalent example of such methods. The foundation images found by PCA depend only on pairwise relationships amongst pixels in the image database. In a task such as face recognition, in which imperative information may be contained in the high-order relationships among pixels, it seems reasonable to expect that better basis images may be found by methods sensitive to these high-order statistics. Independent component analysis (ICA), a generalization of PCA, is one such technique. We used a version of ICA for recognition of faces. ICA was performed on face images in the database, ICA representations were superior as compare to the representations based on PCA for recognizing faces across days and changes in expression. Results shows that a classifier that use ICA representations, gave the best performance.**

Keywords–**Face recognition, ICA, PCA**

I. INTRODUCTION

Face recognition systems are part of facial image processing applications and their significance as a research area are increasing recently. They use biometric information of the humans and are applicable easily instead of fingerprint, iris, signature etc., because these types of biometrics are not much suitable for non-collaborative people. Face recognition systems are usually applied and preferred for people and security cameras in metropolitan life. These systems can be used for crime prevention, video surveillance, person verification, and similar security activities.

Face Recognition is something that human beings usually performs with less effort and without much sensible thought, although it seems to be a challenging problem in the field of computer vision, where some 20 years of research is just beginning to yield useful technological solutions. Face recognition system is a complex image processing problem in real world applications with complex effects of illumination, occlusion, and imaging condition on the live images. It is a combination of face detection and recognition techniques in image analyzes. Recognition algorithm is used to classify given images with known structured properties, which are used commonly in most of the computer vision applications. Recognition applications uses standard images, and detection algorithms detect the faces and extract face images which include eyes, eyebrows, nose, and mouth.

The steps for face recognition system is given below:

- The first step for face recognition system is to acquire an image.
- Second step is face detection from the acquired image.
- Third step, face recognition that takes the face images from output of detection part.
- Final step is person identity as a result of recognition part.

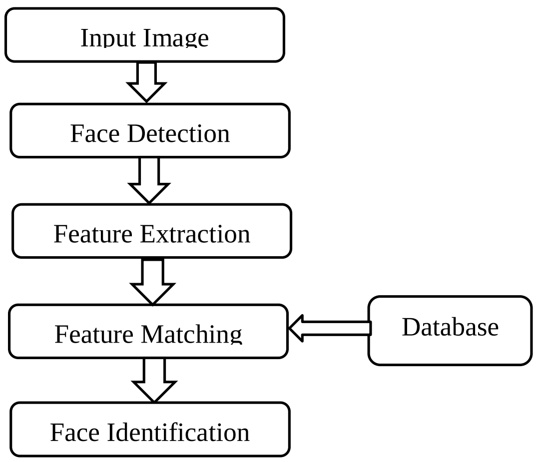

Fig.1: Face Recognition System

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Research in the field of face recognition ongoing in 1960.s with the original effort of Bledsoe [6]. In the 1960s, the leading semi-automated model for face recognition was introduced which work on the location of the topographies such as nose, mouth, and ears on the pictures and then estimate the distances and ratios to a shared reference point. This fact then matched to stored data in the record. Goldstein, Lesk [7] and Harmon in 1970s refers the use of 21 precise individual symbols such as hair colour, lip thickness, etc. to achieve recognition. ut the problem with above mentioned solutions was the huge calculation of the dimensions and locations. But Kanade paper [8] during 1977 get rid of this prblem by developing first fully functional automated face recognition system. The foremost milestone in face recognition introduced in 1988, by Kirby and Sirovich [9] who applied a standard linear algebra method known as principle component analysis. ICA is a modified form of PCA and is considered to have more representative power than PCA. The technique of ICA, although not yet the name, was introduced in the early 1980s by J. H´erault, C. Jutten, and B. Ans [10]. In ICA a linear transformation is determined to represent a set of random variables as linear combinations of statistically independent source variables.

A. *Principle Component Analysis*

PCA aims to determine a new orthogonal basis vector set that best reconstructs the face images, in other words with the smallest mean-square error for any given subspace dimensionality. These orthogonal basis vectors, also called eigenfaces, are the eigenvectors of the covariance matrix of the face images. The most parsimonious eigenvector set, say of dimension M, for the face reconstruction problem is chosen as the subset of the M most energetic eigenvectors that is the eigenvectors corresponding to the first M rank ordered eigenvalues.

Consider the $K \times D$-dimensional face data matrix X, where each D-dimensional row corresponds to the lexicographically ordered pixels of one of the faces, and where there are K face images. The PCA method tries to approximate this face space using an M-dimensional feature vector, that is using M eigenfaces, where typically$M \ll \min(D, K)$. These M eigenvectors span a face subspace, such that $\|X\|^2 - \|XV\|^2$is minimum, where V is the $D \times M$-dimensional matrix that contains orthogonal basis vectors of the face space in its columns. Once the projection bases V are formed, when a test image x_t arrives, it is projected onto the face subspace to yield the feature vector, $r_t = x_t V$. The classifier decides for the identity of the individual, according to a similarity score between r_t and the feature vectors of the individuals in the database, $\{r_1, r_2, \dots, r_K\}$ [5].

B. *Independent Component Analysis*

ICA is the unsupervised computational and statistical method for discovering intrinsic hidden factors in the data. ICA exploits higher-order statistical dependencies among data and discovers a generative model for the observed multidimensional data. In the ICA model, observed data variables are assumed to be linear mixtures of some unknown independent sources (independent components). A mixing system is also assumed to be unknown. Independent components are assumed to be non-Gaussian and mutually statistically independent. ICA can be applied to feature extraction from data patterns representing time series, images or other media.

The ICA model assumes that the observed sensory signals x_i are given as the pattern vectors$X = [x_1, x_2, \cdots, x_n]^T \in R^n$. The sample of observed patterns are given as a set of N pattern vectors$T = \{x_1, x_2, \cdots, x_n\}$that can be represented as a $n \times N$ data set matrix $X = [x_1, x_2, \cdots, x_n] \in R^{n \times N}$ which contains patterns as its columns. The ICA model for the element xi is given as linear mixtures of m source independent variables s_j

$$x_i = \sum_{j=1}^{m} h_{ij} s_j, \quad i = 1, 2, \dots, n$$

Where x_i is observed variable, s_j is the independent component (source signals) and h_{ij} are mixing coefficients. The independent source variables constitute the source vector (source pattern) vectors $s = [s_1, s_2, \cdots, s_n]^T \in R^m$. Hence, the ICA model can be presented in the matrix form

$$\mathrm{x} = Hs$$

Where $H \in R^{n \times m}$ is $n \times m$ unknown mixing matrix where row vector $h_i = [h_{i1}, h_{i2}, \cdots, h_{im}]$ represents mixing coefficients for observed signalx_i. Denoting by h_{ci} columns of matrix H we can write

$$\mathrm{x} = \sum_{i=1}^{m} h_{ci}, s_i$$

The purpose of ICA is to estimate both the mixing matrix H and the sources (independent components) s using sets of observed vectors x. The ICA model for the set of N patterns x, represented as columns in matrix X, can be given as, $X = HS$ Where $S = [s_1, s_2, \cdots, s_n]$ is the m × N matrix which columns correspond to independent component vectors s_i =

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$[s_{i1}, s_{i2}, \cdots, s_{im}]^T$ discovered from the observation vector xi. Once the mixing matrix H has been estimated, we can compute its inverse $B = H^{-1}$, and then the independent component for the observation vector x can be computed by, $s = Bx$ The extracted independent components s_i are as independent as possible, evaluated by an information-theoretic cost criterion such as minimum Kulback-Leibler divergence kurtosis, negenropy.

- *Preprocessing*

Usually ICA is preceded by preprocessing, including centering and whitening.

Centering

Centering of x is the process of subtracting its mean vector $\mu = E\{x\}$ from x:

$$x = x - E\{x\}$$

Whitening (sphering)

The second frequent preprocessing step in ICA is decorrelating (and possibly dimensionality reducing), called whitening. In whitening the sensor signal vector x is transformed using formula

$$y = Wx, \quad so\ E\{yy^T\} = I_l,$$

Where $y \in R^l$, is the $l - dimensional\ (l \cdot n)$ whitened vector, and W is $l \times n$ whitening matrix. The purpose of whitening is to transform the observed vector x linearly so that we obtain a new vector y (which is white) which elements are uncorrelated and their variances are equal to unity. Whitening allows also dimensionality reduction, by projecting of x onto first l eigenvectors of the covariance matrix of x.

Whitening is usually realized using the Eigen-value decomposition (EVD) of the covariance matrix $E\{yy^T\} \in R^{n \times N}$ of observed vector x

$$R_{xx} = E\{xx^T\} = E_x \Lambda_x^{1/2} \Lambda_x^{1/2} E_x^T$$

Here, $Ex \in R^{n \times n}$ is the orthogonal matrix of eigenvectors of $R_{xx} = E\{xx^T\}$ and Λ is the diagonal matrix of its eigenvalues

$$\Lambda_x = diag(\lambda_1, \lambda_2, .., \lambda_n)$$

With positive eigenvalues $\lambda_1 \geq \lambda_2 \geq .. \geq \lambda_n \geq 0$. The whitening matrix can be computed as

$$W = \Lambda_x^{-1/2} E_x^T$$

And consequently the whitening operation can be realized using formula

$$y = \Lambda_x^{-1/2} E_x^T \ x = Wx$$

Recalling that, $x = Hs$, we can find from the above equation that

$$y = \Lambda_x^{-1/2} E_x^T \ Hs = H_\omega s$$

We can see that whitening transforms the original mixing matrix H into a new one, H_ω

$$H_\omega = \Lambda_x^{-1/2} E_x^T \ H$$

Whitening makes it possible to reduce the dimensionality of the whitened vector, by projecting observed vector into first $l\ (l \leq n)$ eigenvectors corresponding to first l eigenvalues $\lambda_1, \lambda_2, .., \lambda_l$ of the covariance matrix, E_x. Then, the resulting dimension of the matrix W is, $l \times n$ and there is reduction of the size of observed transformed vector y from n to l.

Output vector of whitening process can be considered as an input to ICA algorithm. The whitened observation vector y is an input to unmixing (separation) operation

$$s = By$$

Where B is an original unmixing matrix. An approximation (reconstruction) of the original observed vector x can be computed as,

$$\tilde{x} = Bs \text{ ,Where, } B = W_\omega^{-1}.$$

For the set of N patterns x forming as columns the matrix X. We can provide the following ICA model

$$X = B\,S$$

Where $S = [s_1, s_2, \cdots, s_n]$ is the $m \times N$ matrix which columns correspond to independent component vectors $s_i = [s_{i1}, s_{i2}, \cdots, s_{im}]^T$ discovered from the observation vector, x_i. Consequently we can find the set S of corresponding independent component vectors as

$$S = B^{-1} X.$$

II. PROPOSED METHODOLOGY

Feature extraction using ICA

In feature extraction which is based on independent component analysis one can consider an independent component s_i as the, i-th feature of the recognized object represented by the observed pattern vector x. The feature pattern can be formed from m independent components of the observed data pattern. The use of ICA for feature extraction is partly motivated by results in neurosciences, revealing that the similar principle of pattern dimensionality can be found in the early processing of sensory data by the brain.

In order to form the ICA patterns we propose the following procedure:

1. Extraction of n_f element feature patterns xf from the recognition objects. Composing the original data set T_f containing N cases $\{x_f^T i.e. c_i\}$. The feature patterns are represented by matrix X_f and corresponding categorical classes are represented by column c.
2. Heuristic reduction of feature patterns from the matrix X_f into n_{fr} element reduced feature patterns x_{fr} (with resulting patterns, X_{fr}). This step could be

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directly possible for example for features computed as singular values of image matrices.

3. Pattern forming through ICA of reduced feature patterns X_{fr} from the data set, x_{fr}.

- Whitening of the data set X_{fr} including reduced feature patterns of dimensionality n_{fr} into n_{frw} element whitened patterns xrfw (projected reduced feature patterns into n_{frw} principal directions).
- Reduction of the whitened patterns x_{frw} into first n_{frwr} element reduced whitened patterns x_{frwr} through projection of reduced feature patterns into first principal directions of data.

4. Computing the unmixing matrix W and computing reduced number n_{icar} of independent components for each pattern x_{frwr} obtained from whitening using ICA (projection patterns x_{frwr} into independent component space).

5. Forming n_{icar} element reduced ICA patterns x_{icar} from corresponding independent components of whitened patterns, with the resulting data set,X_{icar} forming a data set T_{icar} containing pattern matrix Xicar and original class column c.

6. Providing rough sets based processing of the set T_{icar} containing ICA patterns, x_{icar}. Discretizing pattern elements and finding relative reducts from setT_{icar}. Choosing one relevant relative reduct. Selecting the elements of patterns x_{icar} corresponding to chosen reduct and forming the final pattern, x_{fin}. Composing the final data set $T_{final\ d}$ containing discrete final patterns $x_{fin,d}$ and class column. Composing the real valued data set T_{fin} from the set T_{icar} choosing elements of real-valued pattern using selected relative reduct.

III. Experimental Results

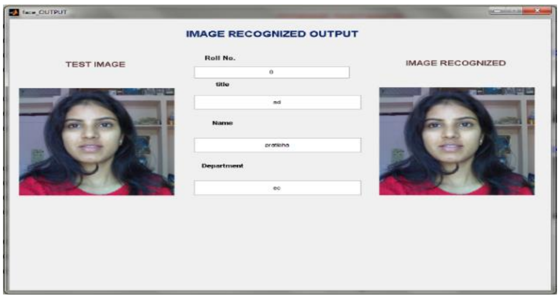

Figure: 2.Output of the face identified

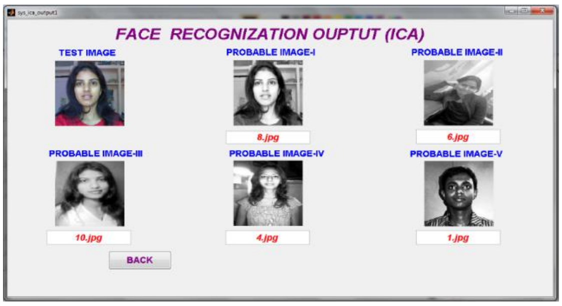

Figure: 3 probable match of face recognize using ICA

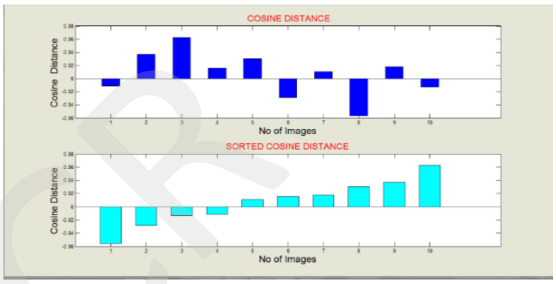

Figure: 4 Euclidean distance of database

IV. Conclusion

ICA is implemented to maximise information transmission in the occurrence of noise, so it is more robust to variations such as lighting conditions, changes in hair, make-up, and facial expression, which are considered as the forms of noise with respect to the main source of information in our face database: the person's identity. The PCA was found to be better in case of angular variations. We use PCA for pre-processing.

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