Independent Component Analysis Based Approach to Biometric Recognition

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***Abstract*—Biometric security systems such as Retina scanner, fingerprint and face recognition among others are the most recently developed security systems. The latest systems can be found in various situations (police checkpoints, airport facilities, . . .). As they become widely used and requested, an increasing number of researchers are working in this field. In this paper, we propose a new Biometric Recognition method based on Independent Component Analysis technique "ICA".**

I. Introduction

In everyday applications, biometric recognition systems should satisfy two major constraints: a perfect reliability in the decision and a trade-off between processing complexity and real-time ability. To reach this purpose, the authors of [1] propose several methods of pattern recognition based on optical correlation.

We should mention that in addition to classical image processing methods, some recent signal processing tools such as ICA have been recently introduced to improve image processing and pattern recognition techniques. Indeed, these powerful techniques are attracting attention of a growing number of researchers and specialists in the image processing field. One of the first applications consists in separating the noises from the useful information "object" in a noised image [2]. Another application consists in encrypting and decrypting a video sequence by mixing together, in a controlled manner, various images of a video sequence [3]. In this latest study an all-optical real-time scheme is proposed. This reason among others is the main motivation of our study.

II. Faces Recognition using FastICA and JADE

In this communication, we propose a face recognition method based on the above cited ICA algorithms. Nowadays, a huge number of ICA methods can be found in the literature. Among these methods, we are mainly interested in two of them: FasctICA [4] and JADE [5]. Indeed, the last two algorithms are used in many applications [6].

Our new technique consists in projecting the target face (to be recognized) onto various independent components previously obtained and recorded in our reference database. In this case, a face recognition step can be reduced to a parametric selection method. Indeed any known face can be characterized using several coefficients related to its projection onto the independent components of our database. A reliable recognition decision can be made by comparing the projection coefficients with those previously obtained.

III. Independent components database construction

In the blind separation of sources (BSS) problem, we can retrieve "p" unknown mixed signals (sources) by only using "q" observed mixing signals [7], [8], [9]. The sources are assumed to be statistically independent of each other [10].

To simplify the discussion and better explain our ideas, we consider firstly that we only have two faces to build. The generalization to n images is straight forward. Let us consider by $s_1(t)$ and $s_2(t)$ the two images where "t" stands for a given pixel.

In this study, only linear mixture has been considered. In this case the mixed images (the face) $x_i(t)$ can be obtained as followed:

$$\begin{aligned} x_1(t) = a_{11} * s_1(t) + a_{12} * s_2(t) \\ x_2(t) = a_{21} * s_1(t) + a_{22} * s_2(t) \end{aligned} \tag{1}$$

where a_{ij} are real or complex coefficients used in order to hide better the information. We should mention here that the linear mixing process can be replaced by a non-linear one.

To easily generalize equation (1) to an arbitrary number of images, we can use the following matricial notation:

$$X(t) = A\left(I(t), \cdots, I(t-L)\right) \tag{2}$$

where $I(t) = \begin{pmatrix} s_1(t) \\ \vdots \\ s_n(t) \end{pmatrix}$ stands for the original images (i.e. the source images), $X(t)$ is the face "mixed images" and A represents the channel effect and it can be any functional operator. It is well known that the latest equation, in generally case (without any assumption about A or $I(t)$), represents a generic problem that can not be solved. In the case of static memoryless channel, equation (2) can be simplified as followed:

$$X(n) = AI(n) \tag{3}$$

In this case, A becomes a real or a complex scalar matrix. This channel is called an instantaneous mixture model. It is well known that the separation of model (3) can be made using ICA techniques based on the independence assumption of sources and can be achieved up to a permutation and a scale factor [10].

As mentioned before (paragraph II), our method is based on the made of the Independent components database knowing the reference faces database (figure 1). In the literature, we can find many algorithms to conduct this separation [8]. These algorithms generally use different approaches:

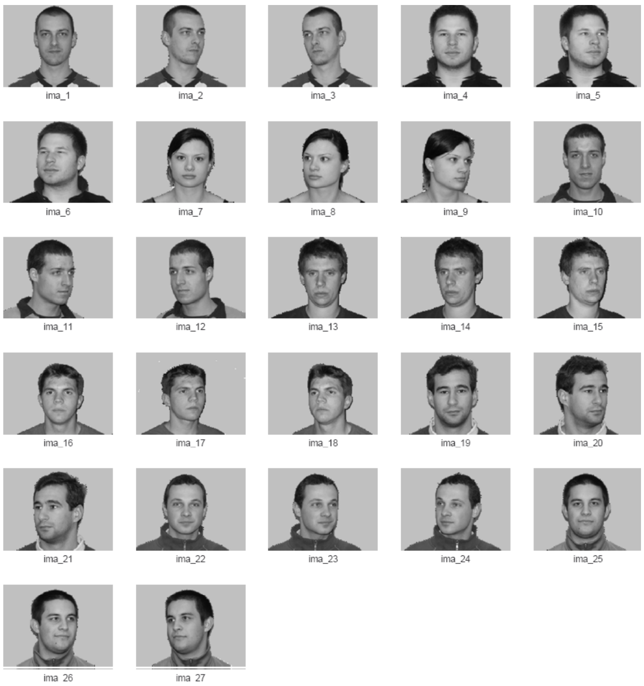

Fig. 1. Example of Face references data-base

- the minimization of a cost function based on High Order Statistics (HOS) [11], [12],
- the maximization of mutual information [13],
- using geometrical concepts [14], *etc.*.

Most of the ICA algorithms deal with the separation of mono-dimensional signals (i.e speech, telecommunication signals, $\cdots$). However, in our application, the sources consist of images. In order to apply ICA algorithms in our application, preprocessing and post-processing steps are required.

In [4], Hyvarinen and Oja proposed an algorithm called FastICA which stands for "Fast Fixed Point Algorithm for Independent Component Analysis". Their algorithm uses the fact that the kurtosis (i.e. a normalized fourth order cumulant [15]) of a Gaussian signal [11], [16] is zero. On the other hand, it is well known that mixing signals generates close to Gaussian signals, as the application of central limit theorem [17].

Some ICA algorithms, such as FASTICA and JADE require two computing stages:

- The first stage is a whitening procedure: Using Principal Component Analysis (PCA) [18] based on second order statistics of observed signals, we can simplify the mixing model by transforming the mixing matrix into a rotation mixing matrix. In fact, it is known that separation matrix A can be decomposed [19] as the product of two matrices $A = WU$, where W is a spatial decorrelation matrix and U is an unitary one. Common [20] proved that we can estimate W by using a simple Cholesky factorization [19] of the covariance matrix of the observed signals.

- Rotation: In this stage, high order statistics [15] criteria can be used to estimate the residual permutation mixing matrix, i.e. U.

We should mention that at the output of the whitening stage the signals are spatially decorrelated. In other words, the correlation matrix of these signals becomes a definite positive diagonal matrix. After the whitening process, one can apply FastICA algorithm to separate the reference faces.

Finally, ICA can be considered as a deflation approach since the algorithm tries to separate the mixing by extracting one signal after another. In their approach, Hyvarinen and Oja suggest the maximization of a contrast function based on a simplified version of the kurtosis. The maximization is done with respect to a norm constraint according to a vector b using a Lagrangian method. Finally the vector b is updated using a gradient algorithm.

As motioned befor, using ICA algorithms and a complete set of users' faces (references figure 1), we can calculate a set of independent components figure(2) and an estimated mixed matrix (which can be used in order to obtain a projection matrix) .

IV. Recognition Method

The independent components of reference faces can be easily obtained by applying any ICA or JADE algorithm using the synoptic diagram presented figure 3.

Fig. 2. Example of independent components data-base

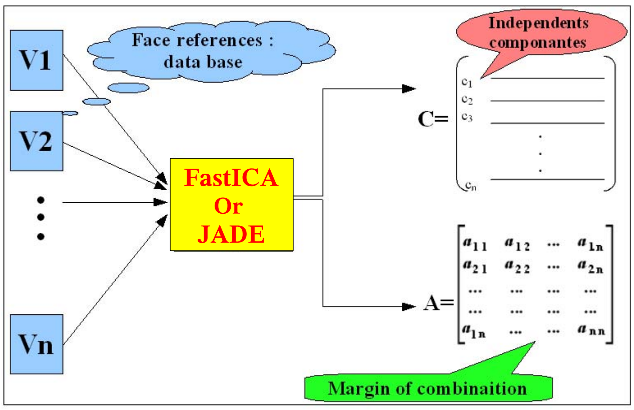

Fig. 3. Determination of independent components and a coefficients matrix

In a second step, a projection of the target face into our database should be performed (figure 4). Further to this projection, a membership relation can be obtained. This membership plays the key role in the recognition step.

V. Results

By considering the face as a linear combination of several independent and primitive image components, we proposed here a new method of face recognition based on independent component analysis and a simple projection technique. In order to obtain our database, we initially used the FastICA method to calculate the independent component database as well as the matrix of mixture "A" (figure 3).

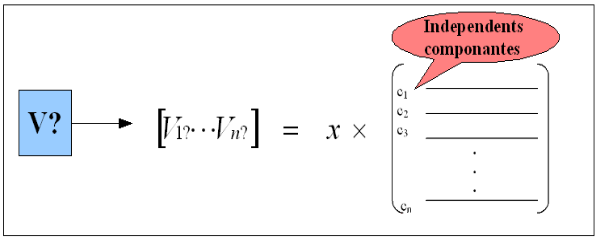

Fig. 4. A synoptic diagram of our proposed method

Originally, 91 faces (size of each one is 160x120 pixels) were considered to construct our database. In order to corroborate the proposed method, many simulations have been conducted in a noise free environment.

Our experimental studies show a recognition error rate of $13.12/100$. Using similar scenario and JADE method, we improve the over-all performances of the method. In fact, an error rate equal to $2.2/100$ was obtained (figure(5)). This very low error rate can promote the proposed method and encourage us to conduct further studies in order to improve and optimize computing efforts and processing time.

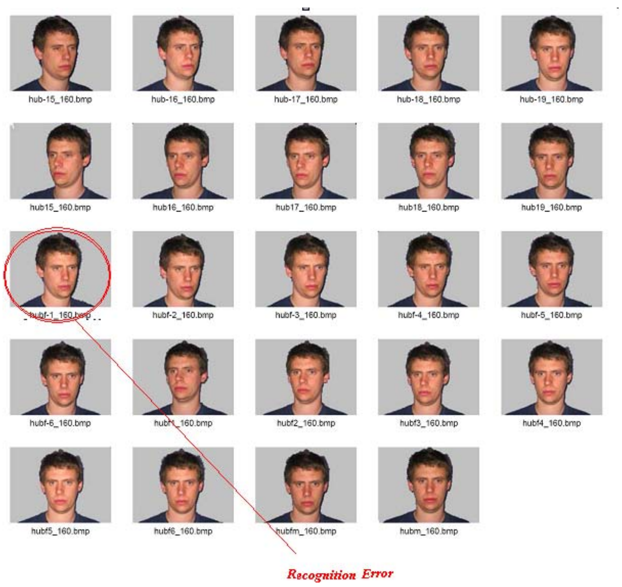

Fig. 5. Example: Input tested faces

VI. Conclusions and Prospects

In this paper, we have proposed and validated the principle of a new method of face recognition using Independent Component Analysis. Thanks to a recognition experiment with JADE, we achieved a great improvement.

In order to go further in the testing of the performance of our method, we will use the False Accept Rate (FAR) and False Reject Rate (FRR) and we will assess our technique with various lighting conditions and/or noise added to the target face (to get as close as possible to real cases).

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