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Appearance based face identification and classification. A Combining approach.

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Abstract—We propose in this paper a search approach which aim to improve identification in biometric databases. We work with face images and we develop appearance-based Eigenfaces method to generate holistic and discriminant features. These feature vectors, which describe faces, are often used to establish the required identity in a recognition process. In this work, we introduce a clustering process which aims to split biometric databases into partitions and to simplify consequently recognition task within these databases. Various studies were undertaken on search strategies to adjust feature extraction and clustering parameters. We simulate four experts which learn differently and acquire various knowledge to recognize facial images. In addition, we evaluate the robustness and the performance of our approach against noise effect through different test series. We propose, finally, to combine and to fuse clustering classifiers and identification processes what improve and simplify our recognition system task.

Keywords—Biometry, face identification, clustering, learning, biometric databases, results fusion.

I. INTRODUCTION

In his daily environment, a person needs to be identified in a multitude of contexts: to enter his building, to reach its place of work, to withdraw money in a distributor, to pay in a store, to reach its data-processing station of work... A wide variety of applications which require reliable recognition schemes to confirm or to establish the identity of an individual. In order to improve identification techniques, research has known for a few years a spectacular revival and a major interest with the biometric data, i.e. with the specific characteristics to each person: her voice, fingerprints, face pattern, hand geometry, signature and even DNA [1]. Thus, techniques based on biometrics enjoy a general passion favoured by an increased request of security.

According to the specifications of a given application, biometric recognition techniques are applied within the framework of authentication or identification process what implies two different modes of research and consultation of the databases. The biometric identification process consists in matching features of the unknown identity with the equivalent templates of all users, already stored in a knowledge base. The unknown person to be recognised or the probe (image containing his face by example) is identified like the user

having the template which resembles the more, according to a given criterion, with the query features (1:N match). We note that the system can act in a closed or an opened universe [2]. In the closed universe, every probe is in the database. Whereas, in an opened universe, unknown people (recorded or not in the knowledge base) could be introduced to the system. Few systems are proposed in the literature treating recognition in opened universe. They proceed with the rejection, in a first step, of faces (subjects) not recorded in the database and keep only the known faces to operate, in a second phase, identification in a closed universe. On the other hand, authentication consists in matching the extracted query features with only those of the proclaimed identity (1:1 match). Here, it is a question of classifying the user like a genuine (true user) or an impostor. Intensive research during these twenty last years pushed this authentication technique which constitutes the base of access control systems to acceptable performances and maturity. However, within the framework of the more general identification, we don't have any priori information concerning the identity of the face. Thus, identification systems have a significant decrease of performances according essentially to the potential number of users of the system (size of the database) under real conditions of application.

To evaluate identification systems we usually seek how good an algorithm is at identifying a probe image (i.e. if the top match is correct). But, in the event of error, it is useful to know if the correct answer is in the top n matches. Then we trace the cumulative match scores which represents the probability that the desired result is among the top n matches [3].

The deployment of biometric solutions in the airports and at countries borders implies gigantic databases at a national scale. In spite of the fast proliferation of these large scale databases, the community of research up to now is concentrated only on the performances in small databases while neglecting questions of scalability and execution speed which are significant for large scale applications. In such applications, the response time and the effectiveness of research become also significant in addition to the precision. Traditional databases classify recorders in an alphabetical or numerical order for an effective research. However, in image databases and especially facial ones, there is no natural order by which we can classify that biometric data. Classification and indexing in these databases constitute the principle challenges to raise [4].

In this paper, we develop face images and especially appearance-based Eigenfaces method to generate holistic and discriminant features and template. These features vectors, which describe faces, are often used to establish the required identity in a recognition process. In this work, we introduce a clustering process which aims to split biometric databases into partitions and to simplify consequently recognition task within these databases. Various studies were undertaken to adjust feature extraction. Several test series are carried out to assess the robustness and the effectiveness of our proposed approach. To finish, we propose to combine and to fuse clustering classifiers and identification processes.

II. EXPERIMENTAL METHODS

A. Principal Component Analysis

Principal component analysis (PCA) [5] is a dimensionality reduction technique based on extracting the desired number of eigenvectors with the highest variance of the multidimensional data. PCA is closely related to the Karhunen-Loève Transform (KLT) [6] which generates an orthogonal basis and decorrelate perfectly data vectors. Kirby and Sirovich [6] proposed in 1990 the use of PCA for face analysis and representation. Their paper was followed by the Eigenfaces technique by Turk and Pentland [7], the first application of PCA to face recognition. Since, several face recognition systems presented in the literature use this appearance-based method [8, 9].

A two dimensional image of size p by q pixels is generally represented as a vector of size n ($n = p \times q$) in high dimensional space. Facial images represented as vectors of samples x can be expressed as linear combinations of the lower dimension orthogonal basis Φ_i :

$$\Phi_i : x = \sum_{i=1}^n a_i \phi_i \approx \sum_{i=1}^m a_i \phi_i \quad (1)$$

The orthogonal basis Φ defines the face space at a lower dimension m ($m \ll n$) by resolving the problem

$$C\Phi = \Phi\Lambda \quad (2)$$

where C is the covariance matrix for input x :

$$C = \sum (x - \bar{x})(x - \bar{x})^T \quad (3)$$

$\Phi = [\phi_1, \dots, \phi_m]^T$ is the eigenvectors matrix of C , and Λ is the associated eigenvalues. Eigenvectors which have the same dimension as the input face images are called eigenfaces. Fig. 1 shows an example of few top eigenfaces.



Figure 1. Five top eigenfaces computed from XM2VTS client set.

B. Identification Process

All images of known faces are projected onto the built face space Φ to find sets of weights that describe the contribution of each image vector. Thus, each face in the Enrolment database is represented by a feature vector of weights obtained by projecting its correspondent image on the face space Φ . If we have several facial images per one identity in the database, we can compute as well one feature vector per image as one template vector per identity. In the first case, a person identity is described by several feature vectors. Whereas in the second case, only one kernel feature vector characterize the person identity. When an unknown image of test is given to identify, that image is projected onto the face space to obtain its set of weights. The identification of the test image is performed by finding the known image in the database to which the weights are closest to the weights of the query image within the meaning of a similarity measurement.

III. CLUSTERING APPROACH

We assume the existence of global facial characteristics which allow to subdivide population into a well separated groups. Research community focuses supervised methods to classify facial images by gender or ethnicity [10, 11]. They used facial features which could be incompatible with the learned distributions. Unlike these approaches, we address, in this work, unsupervised classification methods to discriminate facial biometric data.

We propose to reduce the search space by partitioning the database into several clusters (so called bins) using the K-Means clustering algorithm. Our biometric feature vectors described above are assimilated to multi-dimensional data points occupying the multi-dimensional face space Φ . Data clustering algorithms have the aim of identifying the sparse and the crowded places of this space and divide consequently the distribution points into groups in such way to minimize the intra class variance and maximize the inter class variance. Clustering problem is then formalised as follows: given the desired number of clusters K and a dataset of N points, and a distance-based measurement function, it is a question of finding a partition of the dataset that minimizes the value of the measurement function [12]. Data points are then assigned to clusters C_i so that each cluster must contain at least one data point; and each data point may belong to one and only one cluster as show the below formulation:

$$\bigcup_{i=1}^K C_i = \Phi \text{ and } C_i \cap C_j = \emptyset, \forall i \neq j \quad (4)$$

Following such binning, the biometric database will be partitioned such that features or templates in each bin are similar and correspond to a statistical class.

Given a facial image to establish the identity of a person, its feature vector is firstly computed and then compared to each class center (so called centroid). In fact, each bin is represented by its centroid. Query identity is potentially found in the closest bin. However, by increasing the number of bins, probability to find the query identity in the closest bin decreases. Thus, to

prevent missing the bin in which lies the query identity, we performed, in a previous work [13], research in the P closest bins. The parameter P is related to the number K of bins and the intrinsic quality of features and related clustering method. The value of P is experimentally determined to assure that any bin containing the search identity is missing.

Unlike this last study, we operate clustering into few bins. Thus, P parameter is easier to estimate. If we perform clustering into three bins, for example, we can retain a subset made of the closest bin ($P = 1$) or a subset resulting from the two closest bins ($P = 2$). Then, we study whether the required identity is in the kept subset. We denote by C-Identification, the step where we look for the nearest bin(s) to the query image. Then, identification process is performed only on the identities belonging to these bins. Unlike Identification process which compares query identity with identities from the whole database, we denote by Sub-Identification the process of identification performed only on identities from the kept database partition.

A very significant point in an indexing problem is to extract pertinent features which constitute the input of the classification process. We distinguish through our experiments the main pertinent features as well for identification task as for clustering task. We assess three adaptive spaces dimensionalities by defining an adaptive number of eigenfaces from the face space Φ .

Thus, we propose to perform clustering followed by identification process. Clustering process aims to split the biometric database into disjoint partitions and to keep a subset from the initial database where the query identity is most probably belonging. This allows to simplify consequently identification task within these databases.

IV. DATA SET

The XM2VTS database is a multimodal database consisting of 2D and 3D facial images, video sequences and speech recordings. Our experiments were performed on the 2D face images from the XM2VTS database [14]. This extended database contains 4 recording sessions of 295 subjects taken over a period of 4 months. Since the data acquisition was distributed over a long period of time, significant variability of appearance of clients, e.g. changes of hair style, facial hair, shape and presence or absence of glasses, is present in the recordings (cf. fig. 2). Two shots per session was recorded what make a total number of eight image per subject. The database is primarily intended for the task of person verification, where an individual asserts his identity.



Figure 2. Sample of images from the XM2VTS database

Lausanne protocol [15] was defined on XM2VTS database especially for authentication assessment. The protocol was designed for an open test scenario where persons, unknown to the system, might claim access. The database was randomly divided into 200 clients, 25 evaluation impostors, and 70 test impostors. On the other hand, client set was divided into three sets: training set, evaluation set, and test set. Two different evaluation configurations were defined. We extend the first configuration to assess our identification system. Then we conceive three other configurations that we detail in the next section.

V. EXPERIMENTAL STRATEGIES

We followed Lausanne protocol to assess our system performances: we use the established client set of 200 persons and we operate in a closed universe. Each person has 8 frontal images: 4 different sessions with 2 images per each session. Then, we divide this set into different subset: the training, the enrolment and the test sets. The training set is used to build the face space. The enrolment set is selected to produce feature vectors and templates of subjects in the database. The test set is selected to simulate our identification tests.

We conceive four different such subdivisions, that we denote experts, in order to show the importance of the learning task (cf. Table 1). Experts differ by the distribution of training and enrolment sets. Thus, each expert will learn differently to extract features and characteristics representing facial images.

We give here the first expert details. Three images of the first shots of the first three sessions were used for training purpose (cf. Table 2). The other three images of the same sessions were used to enrol the identity in the knowledge database. The last two image of the fourth session were used for the classification and identification tests. Thus, we have a set of 600 training images, a set of 600 enrolment images and a set of 400 images for tests.

TABLE I. DATABASE SUBDIVISION – SEARCHING STRATEGIES

Expert 1	Expert 2
Train - Enrol - Test 600 - 600 - 400	Train - Enrol - Test 800 - 800
Expert 3	Expert 4
Train - Enrol - Test 1200 - 400	Train - Enrol - Test 1600 - 800

TABLE II. EXPERT 1 DATASET PARTITIONNING

Expert 1	Session				
	1	2	3	4	
Shot	1	Training	Training	Training	Test
	2	Enrolment	Enrolment	Enrolment	Test

The first and the third experts are based on a training set from facial images of the first three sessions whereas expert two and four learn from a selected set from the four sessions. One can affirm that these two last experts (2 and 4) have certainly a more significant detail level of an individual facial image from the database than the two other experts (1 and 3). Indeed, facial images of the all four sessions enrich the knowledge of these experts 2 and 4. However, we see through experiments and through following results that the size of the training set has a greater effect than the richness of the training set with more multi-session facial images.

VI. RESULTS

A. Pertinent feature vector

To evaluate identification systems we usually seek how good an algorithm is at identifying a probe image (i.e. if the top match is correct). But, in the event of error, it is useful to know if the correct answer is in the top n matches. Then we trace the cumulative match scores (cf Fig. 3) which represents the probability that the desired result is among the top n matches [3].

We illustrate mainly, in this part, identification rate and the top matches rank i.e. the response number from which we have 100% of identification rate (cf Fig. 3). These two measures allow us to choice pertinent features for both identification and clustering processes.

First, PCA is performed on the original training database. We keep eigenfaces (principal components) which define a percentage of the total inertia. Indeed, we compute the inertia of each eigenfaces relatively to its eigenvalue as below:

$$\frac{\lambda_j}{\sum_{i=1}^n \lambda_i} \quad (5)$$

where λ_j is the eigenvalue associated to the j^{th} eigenfaces.

The total inertia of the j^{th} first eigenfaces is defined by (6):

$$\frac{\sum_{i=1}^j \lambda_i}{\sum_{i=1}^n \lambda_i} \quad (6)$$

We assess different face space sizes and keep first eigenfaces which define 80%, 85% and 90% of the total inertia. For the expert 1, for example, these inertia rates are obtained with 44, 66 and 105 eigenvectors respectively what correspond to feature sizes (see table 3).

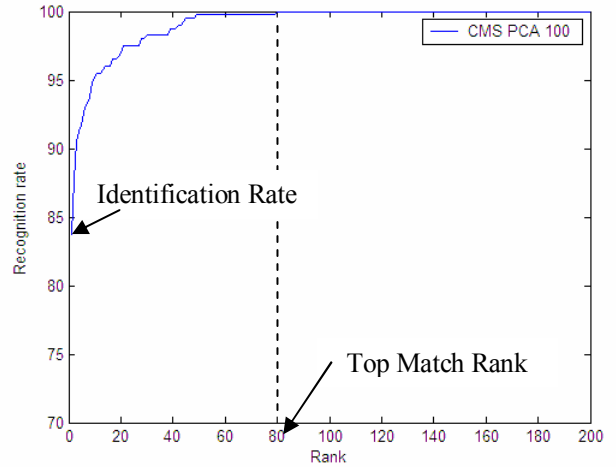


Figure 3. Cumulating match Scores (CMS) with a feature vector of 100 components - expert 1.

Table 3 shows, identification rate and the top matches rank performances of Eigenfaces recognition method for various feature vector sizes and for all experts. We seek feature vectors maximizing the identification rate and minimizing the top matches rank.

We obtain best recognition rate with feature vectors corresponding to 90% of the total inertia of the face space. A rather smallest feature vector size provides worst recognition rate. On the other hand, we remark that recognition rate increase significantly through the four experts due to the richness and the size of the training set. Indeed, we used training dataset of 600, 800, 1200 and 1600 images for the first, the second, the third and the fourth expert respectively. Furthermore, the use of facial images of four sessions for the second expert training, adds nothing compared to the first expert. In fact, expert one's performances are obtained with a training set of only three sessions recording images. One can argue, that XM2VTS database does not contain enough appearance changes through sessions since it was taken in well controlled conditions.

However, while considering the top match rank of the system, we don't have a clear dynamic by the different experts. For example, smallest feature vectors provide a better top match rank performances for the third expert, while the reverse is true for the fourth expert. If we consider that we have as many clusters as subject or identity in the database, the top match rank define top clusters in which lie the query identity. We experiment in the following section the k-means clustering method to classify identities and to reduce the search space.

TABLE III. IDENTIFICATION RATE AND TOP MATCH RANK OF DIFFERENT EXPERTS

Learn	Expert 1			Expert 2			Expert 3			Expert 4		
	80%	85%	90%	80%	85%	90%	80%	85%	90%	80%	85%	90%
PCA Inertia	80%	85%	90%	80%	85%	90%	80%	85%	90%	80%	85%	90%
Features sizes	44	66	105	45	69	113	46	71	119	47	73	125
Identification Rate	77.25	80.5	84	75.13	78.5	81.38	81.5	87.5	89.5	96.13	97.63	98.88
Top matches rank	89	77	86	108	95	100	103	133	125	43	28	21
time : Learn (Off Line)	7.45	7.51	7.65	8.77	8.81	9.05	20.7	20.8	20.9	46	45.8	44.9
Identification	2.38	2.6	3.08	5.45	5.95	6.9	2.38	2.66	3.21	6.23	6.54	7.36

B. Clustering results

We performed clustering in two and three bins. We show in the below table statistics of the kept identities from the closest bin(s). For the clustering into two bins, we give the maximum and the minimum population of bins and the mean number of identities in the retained subset. For the three bins clustering, we show the same statistics by keeping either one bin ($P=1$) or the two closest bins ($P=2$) as a retained subset.

Switch the kept database subset defined from closest cluster(s), answers are as below:

- “Right”: the query image identity belongs to the kept database subset.
- “False”: the query image identity doesn’t belong to this subset.

Then, C-Identification rate is computed as the rapport between the number of right matches and the total query image number. We developed the same features defined above for Identification purpose. Table 5 presents the C-Identification rate, obtained by Eigenfaces feature vectors and K-means clustering algorithm.

We remark that feature vectors perform similarly for each expert. We opt, in this case, for smallest features which imply a reduced space dimensionality for the clustering problem. Thus, we extend experimentation to smaller features. We see clearly through the curves that C-Identification rate is almost the same for a given expert and for various feature vector sizes. The first rate value with 21% of total inertia correspond to a feature of one attribute. We show in the table 5, eigenfaces feature vector sizes of the first expert and for various inertia percentages.

TABLE IV. STATISTICS OF THE KEPT IDENTITIES FROM THE CLOSEST BINS

	Max	Min	Mean of kept identities
K=2	126	74	109
K=3	P=1	104	42
	P=2		

TABLE V. PCA FEATURE SIZES OF THE FIRST EXPERT AND FOR VARIOUS INERTIA.

PCA Inertia	21%	30%	42%	50%	60%	70%	75%	80%	85%	90%
Feature size	1	2	4	6	11	22	30	44	66	105

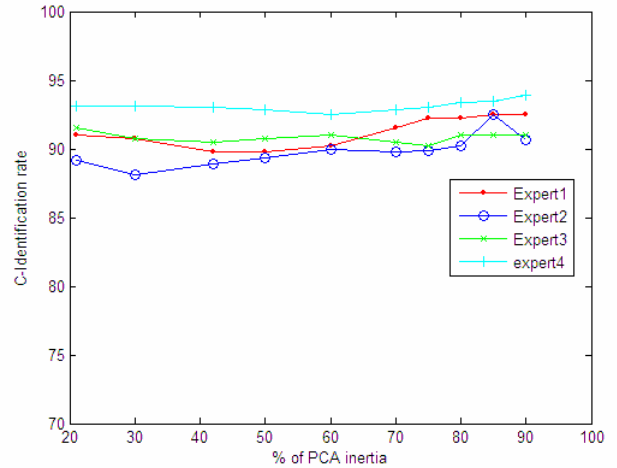


Figure 4. C-Identification rates with various feature vector sizes for the four experts.

We propose, on the other hand, to combine in cascade clustering and identification. Table 6 shows all experts results for different feature sizes. Unlike C-Identification results, Sub-Identification performs better with more complete feature vectors resulting from 90% of the eigenfaces inertia. In addition, we have a consequent gain in computing time between Identification process (cf table 3) and both C-Identification and Sub-Identification processes (cf table 6). These results lead us to propose a new strategy. The first clustering step (C-Identification) will use Eigenfaces method with a short feature vector. Then, identification step will use rather a complete feature vectors with 90% of eigenfaces inertia.

We remark that the Sub-Identification rate doesn’t exceed C-Identification rate. In fact, some identities are misclassified and false matched by the C-Identification process. We study, in the next section, noise effect on our result.

TABLE VI. C-IDENTIFICATION AND IDENTIFICATION RATE WITHIN THE KEPT PARTITION

Learn		Expert 1			Expert 2			Expert 3			Expert 4		
PCA Inertia		80%	85%	90%	80%	85%	90%	80%	85%	90%	80%	85%	90%
K=2	Features size	44	66	105	45	69	113	46	71	119	47	73	125
	C-Identification rate	92.25	92.5	92.5	90.25	90.38	90.63	91	91	91	93.3	93.5	93.8
	Sub-Identification rate	73	75.75	78.75	70.13	73.5	75.88	76.75	80.75	82.5	90.2	91.7	93.1
time : Learn (Off Line)		7.58	7.55	7.61	8.99	9.28	8.94	22	22.1	22	44.7	44.4	44.3
Identification		1.89	2.03	2.25	3.77	4.1	4.71	2.03	2.17	2.53	4.13	4.54	5.16
K=3 P=1	C-Identification rate	86.25	86.25	86.5	86.88	86.75	87.25	86	86.75	86.5	87.5	88	88
	Sub-Identification rate	70	72.25	75	61.25	56.25	60	56.75	58.75	59.75	60.5	62	62
K=3 P=2	C-Identification rate	98.5	98.25	98.25	98.88	98.88	98.63	99	99	99	99.5	99.5	99.5
	Sub-Identification rate	76.25	79	82.5	74.63	78.13	80.63	81.75	86.5	89	95	97	97

TABLE VII. IDENTIFICATION PERFORMANCES OF DISTURBED FACIAL IMAGES WITH SEVERAL DEGREES NOISE

Number of noisy pixels	0	16	64	256	400	576	1024	2025
% of Noise per image	0	0.4%	1.6%	6.2%	10%	14%	25%	50%
Identification Rate	98.83	98.67	98.67	98.67	98.5	97.83	97.5	83.17
C-Identification rate	93.67	93.33	93.33	91.83	91	90.17	83.33	78.83
Sub-Identification rate	93.33	92.67	92.83	91.5	89.83	88.17	79	68.83

C. Noise effect

To evaluate the robustness and the performance of our approach against noise effect, we performed another test series feature vectors with 105 attributes. We took the most trained fourth expert which make the most powerful decision. We disturbed facial images with random grey level noisy pixels. Table 7 shows results of Identification, C-Identification and Sub-Identification on query facial images disturbed at several levels of noise.

We remark that a sparse random noise up to 10% of the image don't affect Identification performance. However, we can go only to 1.6% of noise before degrade Clustering results. Beyond that, we register a decline in C-Identification rate and especially Sub-Identification rate which accumulate clustering and identification false matching results.

D. Fusion scheme

We propose finally, a parallel fusion scheme and a decision maker protocol determining the searched identity or simplifying the search database in the worst case.

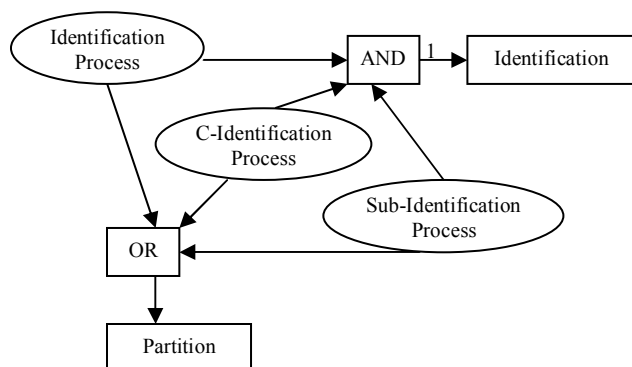


Figure 5. Fusing scheme

Fig. 5 summarizes fusing approach. We use simply the AND/OR fusion rules. In the case where Identification process give the same response that Sub-Identification one, we operate an AND rule and the system return an identity response. However, in the opposite case and if the identity returned by the Identification process doesn't exist in the kept subset, we proceed to do an OR fusion rule to keep a partition which contain potentially the searched identity. We developed this fusing scheme on the first expert. We obtain 78.5% of right identification (AND rule). In the other cases, we perform a new subset constituted from the elaborated subset issued from the clustering task and the identity returned by the Identification process. We miss only 9 query images from a set of 400 query faces. We have only 2.25% of false matching rate.

VII. CONCLUSION AND PERSPECTIVES

We have proposed in this paper a framework of clustering and partitioning face biometric databases. Clustering was achieved on Eigenfaces features using the k-means clustering algorithm. Our future work involves to implement and to combine with Eigenfaces other representation method and other modalities. In the other hand, we have to test other clustering methods and to look for optimal number of classes. We plan also to extend the evaluation of our recognition algorithms with a large scale database gathered from various face databases.

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