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On solving the face recognition problem with one training sample per subject

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Abstract

The lack of adequate training samples and the considerable variations observed in the available image collections due to aging, illumination and pose variations are the two key technical barriers that appearance-based face recognition solutions have to overcome. It is a well-documented fact that their performance deteriorates rapidly when the number of training samples is smaller than the dimensionality of the image space. This is especially true for face recognition applications where only one training sample per subject is available. In this paper, a recognition framework based on the concept of the so-called generic learning is introduced as an attempt to boost the performance of traditional appearance-based recognition solutions in the one training sample application scenario. Different from contemporary approaches, the proposed solution learns the intrinsic properties of the subjects to be recognized using a generic training database which consists of images from subjects other than those under consideration. Many state-of-the-art face recognition solutions can be readily integrated in the proposed framework. A novel multi-learner framework is also proposed to further boost recognition performance.

Extensive experimentation reported in the paper suggests that the proposed framework provides a comprehensive solution and achieves lower error recognition rate when considered in the context of one training sample face recognition problem.

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Keywords

Face recognition

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1\. Introduction

Face recognition (FR) has been an active research area in the past two decades with a lot of encouraging results reported in literature [1], [2]. However, it still remains a difficult problem far from being solved. This is due to the fact that 2-D image representations of the human faces exhibit large variations due to illumination, expression, pose and aging variations. At the same time, image examples available for training face recognition machines are limited which makes the task of characterizing subjects? intrinsic properties a difficult one.

Among the various FR methodologies, appearance-based approaches which treat the face image as a holistic pattern seem to be the most successful [3] with the methods such as the well-known principal component analysis (PCA) [4] (an unsupervised learning technique) and linear discriminant analysis (LDA) [5], [6], [7], [8], [9] (a supervised learning technique) dominating the literature. However, when it comes to realistic FR applications, appearance-based methodologies often suffer from the so-called small sample size (SSS) problem where the number of training samples is much smaller than the dimensionality of the image space [10], [11]. In such an application scenario, the problem of estimating the intra- and inter-scatter matrices needed for recognition becomes either ill- or poorly posed [11].

The one training sample per subject problem can be viewed as an extreme SSS problem that severely challenges conventional FR procedures. It is not hard to see that in such a case, supervised learning techniques may not be applicable since the intra-subject information cannot be obtained from one training sample. However, the one training sample problem is a realistic problem which exists in many FR applications such as surveillance photo identification, forensic identification and access control. One possible solution is to apply an unsupervised technique on the given samples (one per subject). In Ref.

[12], an extension of the standard PCA was proposed, denoted as projection-combined PCA ((PC)2A). The proposal introduced a novel pre-processing scheme by combining the original image with its first-order projection map followed by a standard PCA. In order to enhance performance, following the introduction of (PC)2A framework, Chen [13] proposed an enhanced (PC)2A solution by including a second-order projection map while Zhang introduced a SVD perturbation in the pre-processing step [14]. All reported better performance compared to that of the standard PCA. In addition, Tan proposed a self-organizing map (SOM) based algorithm [15] to solve the one training sample face recognition problem. As stated in Ref. [15], the SOM algorithm can extract local facial features even with a single image sample due to its unsupervised, nonparametric nature, resulting in a lower recognition error rate compared to PCA. However, the performance of these approaches was evaluated using frontal face patterns where only small variations are considered. If more complex variations such as aging-, illumination- and pose-variations are included, the recognition performance is still in question [16].

A different approach to this problem is to artificially generate extra samples for each subject under consideration. In Ref. [17], Huang et al. proposed a scheme to construct local facial feature bunches by moving the original image in four directions. In the method presented in Ref. [18], the sample size for each subject was increased by partitioning a single face image into a set of non-overlapping facial blocks. With the available extra training samples, traditional LDA-style based techniques were applied. However, as indicated in Ref. [19], the generated facial images are highly correlated and should not be considered as truly independent training samples, i.e., the created variations are usually not large enough to cover those observed in reality. Given the 3-D nature of the human face, in Ref. [20], a 2D-to-3D reconstruction approach was proposed in the hope that the generated virtual faces with their illumination-, expression- and pose-variations will allow for the effective application of a traditional PCA or LDA solution. However, such implementation is very complex and computationally demanding given the fact that 3-D model should be constructed. In such a case, some of the facial feature points such as eyes, nose tip and mouth should be located accurately, which is an unrealistic requirement in practice.

In this paper, we introduced the so-called generic learning (GL) framework in an attempt to address the one training sample problem. In the GL-based recognition system, the training of appearance-based algorithms is performed using a generic database which contains subjects different from those to be identified. The learning machine is trained to extract discriminant information from subjects other than those that will be called to recognize when in operation. The principle behind the framework is that the discriminant information pertinent to the specific subjects (those to be identified) could be learnt from other subjects due to the fact that human faces exhibit similar intra-subject variations [21]. This well understood principle is driving the popular Bayes recognition engine [22] or the unsupervised, PCA-like, solutions. As a matter of fact, PCA can be viewed as a generic learning technique since its implementation does not require the information regarding underlying class structure of the data. In other words, it does not target the specific classes. The Bayesian solution for face recognition [22] is also a generic learning technique. It treats the recognition as a two class classification problem, inter-subject variation class and intra-subject variation class, without specifying such variation belongs to which specific subjects. In addition, the idea of generic learning has been proposed

previously as a potential candidate in solving the one training sample recognition problem. In Ref. [19], the expression-invariant subspace is learnt by training a PCA machine on the expression-varied images from a set of subjects different from those under consideration. The method in Ref. [23] solves the free pose face recognition problem from a single frontal face image by collecting a generic data set to extract a view-invariant subspace for the locally LDA engine. Wang et al. [16] proposed a solution to the one training sample problem by introducing a feature selection mechanism in the feature space obtained by applying the PCA technique on a generic database.
Since the collection of a generic database is controlled by the system designer, it is reasonable to assume that at least two image samples are available for each generic subject. Therefore, any available appearance-based FR methodology can be readily integrated within the proposed framework. To the authors? knowledge, a complete and systematic examination of the performance of the state-of-the-art FR methodologies using a generic training set is not available. In this paper, extensive experimentation is used to determine how the state-of-the-art FR methodologies function within the generic learning framework. The results reported here could be used to determine what specific FR procedure should be used to solve the one training sample recognition problem. A multi-learner framework is proposed to boost the generic performance when a large-scale generic database is available. It is well known that when a large training set and a large number of subjects are considered, the recognition performance of appearance-based FR techniques, especially that of linear approaches, deteriorates due to the fact that the distribution of face patterns are no longer convex as assumed by linear models. To enhance performance, the so-called principle of ?divide and conquer? is invoked. According to it, the large-scale generic database is decomposed into small subsets. A set of FR subsystems are then generated using the generic database components. The final result is then obtained by aggregating the outputs of the various FR subsystems. Extensive experimental results suggest that the proposed multi-learner framework significantly improves the recognition performance when a large-scale generic database is available.
The rest of the paper is organized as follows: Section 2 formulates the face recognition problem under the one training sample scenario and describes the generic learning framework; in Section 3, a set of state-of-the-art appearance-based FR solutions which are to be integrated in the generic learning framework are briefly reviewed for completeness. A multi-leaner framework to improve the recognition performance is introduced in Section 4 with the description of framework design and the discussion of combination strategies. Extensive experimentations are presented in Section 5 followed by a conclusion drawn in Section 6.

2. Generic learning framework

A one training sample face recognition problem can be formulated as follows: Let $S=\{S_i\}_{i=1}^{H}$ be the identity label set of _H_ subjects of interest. Let $G=\{g_i\}_{i=1}^{H}$, denoted as _gallery_ , be a set of prototypes consisting of _H_ face images, each of which is corresponding to a different subject of interest, i.e., $ID(g_i)=S_i, i=1,?,H$, where $ID(\cdot)$ represents the corresponding identity. Let p be the unknown face image to be identified, denoted as _probe_. In appearance-based learning methodologies, each face image is represented as a column vector of length $J(=I_w\times I_h)$ by lexicographic ordering of the pixel elements, i.e., $g_i,p?R^J$, where $(I_w\times I_h)$ is the image size, and R^J denotes the J-dimensional real space. Thus the objective of an FR task is to determine the identity of p, i.e., $ID(p)$, where $ID(p)?\{S_1,?,S_H\}$.
Within the generic learning framework, the FR system is built through training

an appearance-based algorithm on a generic database which contains subjects different from those of interest. Let Z={Zi}i=1C be the generic database, containing _C_ subjects with each subject Zi={zij}j=1Ci, consisting of Ci face images zij with a total of N=?i=1CCi face images available in the database, where zij?RJ. The subjects in the generic database do not overlap with those of interest, i.e., ID(Z)?S=?. In the training session, a feature subspace is extracted through training a feature extraction algorithm on the generic database. In appearance-based FR solutions, the objective of feature extraction is to find a transformation ? based on optimization of certain separability criteria, which produces a low-dimensional feature representation yij=?(zij) intrinsic to face objects, where yij?RF and ?F?J. While in the operation session, both gallery samples G and the probe p are projected into the feature space to get the corresponding feature representations. A nearest neighbor classifier is then applied to determine the identity of p by comparing the distances between p and G in the feature space. The identity is then determined as the one with the smallest distance, i.e.,(1)ID(p)=ID(gi*),i*=argmini=1H??(p)-?(gi)?,where ?·? denotes the distance metric. Fig. 1 depicts the diagram of the generic learning framework.

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Fig. 1. Generic learning framework.

The generic learning framework is a realistic solution to the one training sample problem, since a reasonably sized generic database is always available. Without the sample size limitation of generic database, the available FR methodologies can be readily integrated in the generic learning framework.

It is well known that there are two key modules in general face recognition system, feature extraction (FE) and classification. In this paper, we focus on the feature extraction module. As for classification, a nearest neighbor classifier is applied for all experiments. The performance of many state-of-the-art feature extraction methodologies have been examined within the generic learning framework. In detail, the following techniques have been evaluated in this paper: PCA [4], IntraBayes (a maximum likelihood version of the Bayes solution [22]), Fisherface method (FLDA) [5], regularized discriminant analysis (RLDA) [11], kernel-PCA (KPCA) [24], generalized discriminant analysis (GDA) [25] and kernel direct discriminant analysis (KDDA) [26]. These techniques are briefly reviewed in the followed section for completeness.

3\. Feature extraction techniques

Feature extraction is one of the most important modules in face recognition system which produces lower dimensional feature representations of the face samples with enhanced discriminatory power for classification purposes. Among various FE solutions, linear techniques are commonly used in literature whose objective is to produce a transformation matrix _A_ transforming the original image space to a lower dimensional feature space, i.e.,(2)?(x)=ATx,x?RJ,?(x)?RF,where _A_ is a J×F transformation matrix. In general, PCA [4], LDA [5] and Bayes Solution [22] are the three most important linear FE techniques. PCA is an unsupervised learning technique which provides an optimal, in the least mean square error sense, representation of the input in a lower dimensional space. It produces the most expressive subspace for face representation but is not necessarily the most discriminating one. This is due to the fact that the underlying class structure of the data is not considered in the PCA technique. LDA, however, is a supervised learning technique which provides a class specific solution. It produces the optimal feature subspace in such a way that the ratio of between-class scatter and within-class scatter (Sb/Sw) is maximized [5]. LDA based solutions are generally believed to be superior to those unsupervised solutions, however, they are more subjectable to the so-called ?SSS? problem where the number of training samples per subject is much smaller than the dimensionality of the face data J=(Iw×Ih). In such a case, Sw is singular, which makes the direct optimization of the ratio Sb/Sw impossible. In order to solve the SSS problem, many strategies have been proposed in literature, such as Fisherface method [5] and regularized discriminant analysis [11]. Bayes solution is also an effective FE technique which produces the intra-subject feature space and inter-subject feature space by maximizing the covariance matrices estimated from the intra-subject difference samples (image difference samples from same subject) and the inter-subject difference samples (image difference samples from different subjects). IntraBayes solution is a maximum likelihood version of the standard Bayes method in which only intra-subject variation is analyzed; however, the performance is still satisfying as reported [22]. Therefore, the recognition is performed by determining whether the image difference of the probe and the gallery sample belong to intra-subject class or not.

Although linear solutions are successful in many cases, as the complexity of the face pattern increases, i.e., more complicated variations are included such as aging and pose variations, they cannot provide satisfying performance. In such a case, nonlinear models are introduced to capture the highly non-convex and complex distribution.

Kernel mechanism is the key component in the available nonlinear FE techniques. The premise behind the kernel based solutions is to find a nonlinear transform from the original image space (RJ) to a high-dimensional feature space F by using a nonlinear function ?(·), i.e., ?:z?RJ->?(z)?F. In the high-dimensional feature space F, the convexity of the distribution is expected to be retained so that a traditional linear methodology can be applied [27], [28]. Without defining the exact representation of the nonlinear function ?(·), it is revealed that the dot product in the feature space F can be replaced by a kernel function k(·) defined in the original image space RJ [27], [28]. Let zi?RJ, zj?RJ be two vectors in the original image space, the dot product of their feature representations ?(zi)?F, ?(zj)?F can be computed by a kernel function defined in RJ, i.e., ?(zi)·?(zj)=k(zi,zj). Therefore, the key task of designing a kernelized FE solution is to represent the linear FE procedure by using dot product forms. Among the available nonlinear FE solutions, KPCA [24], GDA [25] and KDDA [26] are the most commonly used techniques.

4\. Multi-learner solution

It is well known in appearance-based FR methodologies, accurate estimation of embedded parameters (e.g., Sb, Sw in LDA based solutions) requires a large number of training samples due to the high-dimensionality of the input space J(=Iw×Ih) [10]. Therefore, a large-scale generic database is required to provide a good generic behavior. However, as the size of the database increases, the distribution of face patterns becomes more complex. In such a case, the available FE techniques, especially for those linear ones, may not be capable of capturing these increased variations, resulting in a performance degradation. A possible solution is to decompose a complex global FR task into a set of simpler local FR subtasks based on the principle of the so called ?divide and conquer? [29]. Therefore, a multi-learner strategy is proposed to further boost the recognition performance.

4.1. Database decomposition

From a designer's point of view, the central issue in a multi-learner system is how to decompose the database into smaller subsets which are used to construct a set of FR subsystems. In this work, we propose a decomposition scheme which randomly samples subjects in the generic database, building new training sets by using the identified subjects and their corresponding images. It is different from the scheme commonly used under the traditional FR scenarios that samples the images for each subject [30], [31], [32]. In the authors? opinion, the proposed scheme is a sound design strategy for the following reasons:

(1) It allows for the combination of many relatively weak recognizers, thus improving inter-subject variation determination and recognition performance. In almost all appearance-based FR solutions, the within- and between-class scatters (Sw and Sb) are the two most important parameters which are used to characterize the intrinsic properties of the intra-subject and inter-subject variations. It is further noticed in Ref. [22] that the orientations of these distributions provide important information, in other words, the eigenvectors of Sw and Sb are the key factors on which FR performance depends. This is usually the case in most FR solutions, where the feature subspace is learned by eigen-analysis of Sw, Sb or St=Sw+Sb and the obtained eigenvectors are used to form the transformation matrix. Therefore, accurate estimation of the Sw and Sb eigenvectors critically affects the recognition performance. In FR applications, the inter-subject variations are expected to be large while the intra-subject variations are expected to be small, meaning that the eigenvectors of Sb with large eigenvalues and the eigenvectors of Sw with small eigenvalues are of most importance. However, the larger in magnitude the eigenvalue is, the higher the estimation variance of the corresponding eigenvector could be and that can negatively impact recognition performance. In the following, we will show this by proving the relationship between the lower bound of the estimation variance of the eigenvector and its corresponding eigenvalue.

Let x1,?,xm be _m_ samples drawn from a Gaussian distribution X?N(?,?), where xi?RJ. Let ei,?i be the corresponding eigenvector and eigenvalue of ?. Thus it can be easily deduced that ?=?i=1F?ieieiT, and ?-1=?i=1F(1/?i)eieiT, where F=rank(?). Therefore, the probability distribution function of f(X) can be expressed as(3)f(X)=1(2?)N/2|?|1/2exp-12(X-?)T?-1(X-?)=Cexp-12?i=1F1?i(X-?)TeieiT(X-?)where C=1/(2?)N/2|?|1/2 is the normalization factor.

Let ?^,?^ be the unbiased estimated mean and covariance matrix, respectively [33], and e^i be the corresponding eigenvector, where(4)?^=1m?i=1mxi,?^=1m-1?i=1m(xi-?^)(xi-?^)T.The corresponding e^i should be also considered an unbiased estimator. Let us define the variance associated with estimating e^i=[e^i1,?,e^iJ] as the sum of the estimation variance for each of its elements, i.e.,(5)var{e^i}=?j=1Jvar{e^ij}.Using the Cramer?Rao lower bound definition in Ref. [34], the estimation variance of _j_ th element of the unbiased estimator e^i is bounded from below as(6)var{e^ij}?[I-1(ei)]jj,where I(ei) is the Fisher Information Matrix, with its (j,k)th element defined as(7)[I(ei)]jk=-E?2logf(X)?eij?eik.With the definition of f(X) in Eq. (3), it can be shown that(8)?2logf(X)?eij?eik=-12?i?2[(X-?)TeieiT(X-?)]?eij?eik=-12?i2(xj-?j)(xk-?k)=-(xj-?j)(xk-?k)?i,where xi,?i denote the ith element of the vector X and ?, respectively. Therefore,(9)[I(ei)]jk=E(xj-?j)(xk-?k)?i,I(ei)=1?i?.Thus the Cramer?Rao lower bound (CRLB) of var{e^ij} is(10)var{e^ij}??i[?-1]jjand(11)var{e^i}=?j=1Jvar{e^ij}??itrace{?-1}=?i?k=1F?k.

It can be observed from Eq. (11) that(12)if:?m>?n,then:?m?k=1F?k>?n?k=1F?k.Thus the CRLB of the estimation variance of the eigenvectors corresponding to larger eigenvalues is greater than that of the eigenvectors corresponding to smaller eigenvalues. In context of FR applications, the most important discriminant information exists in the subspace specified by the significant eigenvectors of Sb corresponding to large eigenvalues. However, according to Eq. (12), the corresponding estimation is not very reliable. The analysis provided supports the authors? claim that inter-subject related information which is estimated from data sets using generic subjects results in weak or unstable recognition procedures in most cases due to the nature of training. Therefore, combining a set of weak learners generated by sampling the generic subjects helps to reduce the variance of the estimation of Sb, and thereafter, improves the recognition performance.

(2) It is robust against overfitting.

As additional subjects and corresponding image samples are included in the generic database, the dimensionality of the extracted feature space (_F_) increases. For example, F=Nsbj-1 for LDA based solutions and F=Nsmpl-1 for PCA based solutions, where Nsbj and Nsmpl denote the number of training subjects and the number of training samples, respectively. From classification's point of view, the dimensionality of the input space increases which introduces more free parameters in the classification model. However, the number of the samples used to train the classifier does not change. This is because the nearest neighbor classifier is trained using the samples available in the gallery set. This could lead to severe overfitting phenomenon resulting in poor performance [33], [35]. Therefore, decomposing the generic database into smaller subsets containing fewer subjects helps to reduce the feature subspace dimensionality, thereafter, the overfitting can be alleviated.

For the reasons explained previously, the overall generic training database is decomposed into _M_ training subsets, each of which contains _S_ subjects randomly selected from the generic database without replacement. While the decomposition scheme is designed, one question should be answered. How to determine the number of subjects in each subset (_S_) and the number of subsets (_M_)? There is no single answer to this question. There is no systematic way to determine these two parameters a priori in order to achieve optimal results in terms of recognition rate. A similar problem exists in clustering applications where the number of clusters has to be determined in advance for example in K-means algorithm [33]. One possible solution is to determine these parameters experimentally using a validation set. Since the focus of this paper is not in designing a clustering solution, the determination of the optimal value for these two parameters is left for future research. However, their influence on the recognition performance is analyzed experimentally and details will be provided in the experiment section.

4.2. Framework design

Fig. 2 depicts the multi-learner framework. Let Tk={Tik}i=1S be the _k_ th generic subset containing _S_ subjects. Each subject Tik={tijk}j=1Sik consists of Sik face images tijk, where tijk?RJ. Therefore, a total of Nk=?i=1SSik images are available in the _k_ th generic subset. In the training session, for each generic subset, a feature extractor is applied independently to produce a corresponding feature subspace specified by a linear or nonlinear mapping ?k(·),k=1,?,M. Let us take PCA as an example, _M_ PCA transformation matrices APCAk,k=1,?,M, are obtained as follows:(13)?PCAk(x)=(APCAk)Tx,APCAk=argmaxA|ATStkA|,Stk=1Nk?i=1S?j=1Sik(tijk-t¯k)(tijk-t¯k)T,t¯k=1Nk?i=1S?j=1Siktijk.

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Fig. 2. Multi-learner framework.

After feature extraction, in real operations, both gallery samples and the probe are projected into these feature subspaces to get the corresponding

feature representations Gk and Pk
i.e.,(14)Gik=?k(gi),Pk=?k(p),i=1,?,H,k=1,?,M.Therefore the probe's identity is determined independently by each of _M_ FR subsystems which is the output of a nearest neighbor classifier applied in the corresponding feature subspace, i.e.,(15)IDk(p)=ID(gi*),k=1,?,M,i*=argmini=1H?Pk-Gik?.The final determination is then obtained by aggregating the outputs of all FR subsystems.

4.3. Combination strategy

The final determination of probe's identity is obtained by combining the decisions from all FR subsystems. In this paper, sum rule and majority vote are selected as the combination strategies for their simplicity and robustness [29], [36].

4.3.1. Measurement transformation

In addition to probe's label, each FR subsystem also outputs some measurements which represent the confidence degree of the corresponding decision. For nearest neighbor classifier, the associated distance between the probe and each gallery sample can be used as a similarity (dissimilarity) measure. The smaller the distance, the higher the confidence that the probe belongs to the corresponding subject. In order to combine these measures, the outputs should be firstly transformed to a unified domain such that they have similar scales and the same physical meaning.

Let dki be the distance between the probe and the gallery sample gi in the _k_ th feature subspace, where i=1,?,H,k=1,?,M. Thus the distances obtained by all FR subsystems are formulated as follows:(16)DG=d11?d1H???dM1?dMH.

In order to convert these distances to the same range, a normalization operator is firstly applied to scale the outputs to zero mean and unit standard deviation [37], i.e.,(17)dki=dki-??,where ? and ? are the mean and variance of all distances dki,i=1,?,H,k=1,?,M. The scaled distances are then transformed to confidence measures by using an activation function. Here a sigmoid function followed by a unity of sum normalization is applied to approximate the posterior probability [37], i.e.,(18)rki=11+exp(dki),rki=rki?i=1Hrki,where rki denotes the class score, approximating the posterior probability p(ID(p)=ID(gi)|p) outputted by the _k_ th FR subsystem.

4.3.2. Combination rules

Sum rule ?The combination by using a sum rule is to sum up the class scores as a final score. The identity is then determined by choosing the one with the largest final score, i.e.,(19)ID(p)=ID(gi*),i*=argmaxiRG-Sumi,RG-Sumi=?k=1Mrki.

Majority vote ?For majority vote rule, each FR subsystem ballots a vote to the subject to which it believes that the probe image belongs. The final identity is therefore determined as the one which receives the majority votes, i.e.,(20)ID(p)=ID(gi*),i*=argmaxiRG-Majorityi,RG-Majorityi=?k=1MI(k,i),I(k,i)=1ifIDk(p)=ID(gi),0otherwise,where IDk(p) is the identity of p outputted by the _k_ th FR subsystem.

With the development of the multi-classifier/learner research, many state-of-the-art combination strategies have been proposed such as rule based schemes [36], order statistics [38] and stacked generalization [39]. However, the focus of this paper is to discuss the generic learning solution to the one training sample problem and the purpose of proposing a multi-learner framework is to improve the generic performance of the available FE techniques when a large-scale database is available. Although only simple combination schemes are utilized in this paper, performance improvement by introducing a multi-learner framework is still obvious from the experiments. Therefore extensive examination of different combination strategies is not included in this paper.

However, how combination schemes further affect the recognition performance is still an important problem under investigation.

5. Experiments and results

In this paper, three sets of experiments have been performed to demonstrate the effectiveness of the generic learning framework under the one training sample scenario. The first experiment is to evaluate the recognition performance of the state-of-the-art feature extraction techniques embedded in the generic learning framework. The second experiment is performed to depict how a multi-learner framework improves the recognition performance when a large generic database is available. In the third experiment, some state-of-the-art one training sample solutions by only using the gallery samples, denoted as specific learning, are performed for comparison purposes.

In order to make the database ? _generic_ ? as well as reasonably sized, the whole data set consisting of 5676 images of 1020 subjects is collected from 5 well-known databases, FERET [40], [41], PIE [42], AR [43], Aging [44] and BioID [45]. Since our work does not include a face detection procedure, all images should be manually aligned and normalized which requires the coordinate information of some facial feature points. The FERET database [40], [41] contains 14,501 images of 1209 subjects. Among them, 3817 images of 1200 subjects are officially provided with the eye location data. In addition, 1016 more images have been manually determined the eye coordinates by the authors. Therefore, altogether 3881 images of 750 subjects with at least 3 images per subject are collected from the FERET database to form the data set. The PIE database [42] was created by the research group from Carnegie Mellon University which contains 41,368 images of 68 subjects. The database covers a wide range of image variations due to different illuminations, poses and expressions. Among them, 3805 images are provided with the coordinate information of facial feature points. From these 3805 images, 816 images of 68 subjects (12/subject) are selected to form our data set. For each subject, seven different poses and five different lighting conditions are included. Following the PIE's naming rule, pose group [27,37,05,29,11,07,09] is selected, which contains both horizontal and vertical rotations. Images with pose variations are under a normal lighting condition and with neutral expressions. For illumination variations, 5 frontal face images with neutral expressions are randomly selected from all 21 different illumination conditions with room lighting on. The AR database was created by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the UAB [43]. It contains over 4000 color images of 126 subjects. The database contains the frontal face images with various facial expressions, illumination conditions, and occlusions (sun glasses and scarf). Currently, 119 subjects with 4 images per subject are provided with the information of eye coordinates. All these 476 images are included in our data set. The FG-NET Aging database [44] was developed as a part of the European Union project FG-NET (Face and Gesture Recognition Research Network). It contains 1002 color/gray scale images of 82 subjects at different ages, each of which is provided with feature point coordinates. Among them, some of the low-quality or extremely difficult recognized images are discarded (e.g., baby images and old adult images are not selected at the same time for a specific subject). Finally 276 images of 63 subjects are included. The BioID database which contains 1521 face images was designed for face detection purposes [45]. However, each subject in the database has more than two image samples which makes it applicable for face recognition applications. Thus 227 images of 20 subjects are selected to form our data set. The detailed configuration of the whole data set is illustrated in Table 1.

Table 1. Data set configuration

Database	No. of subjects selected	No. of images per subject	No. of images selected
FERET	750	?3	3881
AR	119	4	476
Aging	63	?3	276
BioID	20	?6	227
PIE	68	12	816
Total	1020	?3	5676

The color images are firstly transformed to gray scale images by taking the luminance component in YCbCr color space. Thus all images are preprocessed according to the recommendation of the FERET protocol, which includes: (1) images are rotated and scaled so that the centers of the eyes are placed on specific pixels and the image size is 150×130; (2) a standard mask is applied to remove non-face portions; (3) histogram equalized and image normalized to have zero mean and unit standard deviation. Then each image is finally represented as a vector of length 17,154.

5.1. Experiment I?generic learning: single feature extractor

The first experiment is to examine the recognition performance of various feature extraction techniques applied on the whole generic database.

5.1.1. Database

From the whole data set which contains the image samples of 1020 subjects, 60 subjects are randomly selected to form a test set to simulate a real FR task, denoted as _TstD_. For each subject, one frontal image with neutral expression is selected to form the gallery of size |G|=60 while the remaining images in the _TstD_ are treated as probes. Therefore, the objective of an FR task is to determine the probe's identity, i.e., which gallery subject the probe belongs to. In the remaining 960 subjects of the data set, SG subjects with the corresponding image samples are randomly selected to form the generic database _GenD_ used for training. In order to examine how the size of generic database affects the recognition performance, a set of experiments are performed corresponding to SG=[60,80,100,150,200,250,300,400,600,800]. In order to increase the experiment accuracy, the selection of _TstD_ is repeated 10 times. In addition, for each specific _TstD_ , the selection of SG subjects to form the _GenD_ is also repeated 10 times. Therefore, altogether 100 repetitions have been made for a specific SG value. The results reported here are the average of all 100 repetitions.

5.1.2. Protocol and setting

The feature subspace is obtained through training a feature extraction algorithm on _GenD_. In this paper, seven different feature extraction techniques are performed, i.e., PCA, IntraBayes (abbreviated as Bayes in the tables and figures), FLDA, RLDA, KDDA, GDA and KPCA. For RLDA approach, the regularization parameter ? is set to 0,1, and 0.001 (a value suggested in Ref. [46]). Thus the corresponding RLDA solutions are denoted as RLDA0,RLDA1 and RLDA?, respectively. For kernel based approaches, radio basis function (RBF) is selected as the kernel function for KDDA, KPCA and GDA, i.e., k(zi,zj)=exp(-?zi-zj?2/?2). The kernel parameter is selected as ?2=108 for all three approaches so that the possible influence due to the kernel parameters can be eliminated.

It is well known that the maximum feature space dimensionality equals to Nsmpl-1 for PCA based solutions and Nsbj-1 for LDA based solutions based on the assumption that the dimensionality of image space is larger than the number of training samples, where Nsmpl is the number of training samples and

Nsbj is the number of training subjects. In addition, RLDA, KDDA and GDA approaches are performed by using the MATLAB code provided by the original authors of Refs. [11], [26], [25], in which some specific schemes are utilized to further reduce the feature space dimensionality by only keeping the significant eigenvectors of the between-class scatter with the corresponding eigenvalues greater than a threshold. As for intra-subject space (IntraBayes), since the covariance matrix of intra-subject image differences (SIntra) is equivalent to the within-class scatter (Sw) [21], the corresponding feature space dimensionality equals to (Nsmpl-Nsbj) [5]. Table 2 lists the maximum feature space dimensionality obtained by different feature extraction techniques, averaged over 100 repetitions.

Table 2. Feature space dimensionality

FE Tech.	No. of subjects/no. of images in generic database									
Empty Cell	60/	80/	100/	150/	200/	250/	300/	400/	600/	800/
Empty Cell	339	447	554	835	1118	1393	1671	2241	3344	4451
PCA	338	446	553	834	1117	1392	1670	2240	3343	4450
Bayes	279	367	454	685	918	1143	1371	1841	2744	3651
FLDA	59	79	99	149	199	249	299	399	599	799
RLDA0,1,?	47	63	79	119	159	199	239	319	479	639
KPCA	338	446	553	834	1117	1392	1670	2240	3343	4450
GDA	59	79	99	149	199	249	299	355	346	341
KDDA	58	68	74	80	82	84	89	89	88	87

In the test, both the gallery images and the probe images are projected into the extracted feature space and a nearest neighbor classifier is applied on the projection coefficients. The identity of the probe is determined by comparing the distances between the probe and each gallery sample in the feature space. Thus the probe belongs to the corresponding gallery subject with the smallest distance. In the PCA- and IntraBayes-based feature spaces, Mahalanobis distance is used for classification for its better performance, while for others Euclidean distance is utilized. Correct recognition rate (CRR) is then evaluated as the measure of recognition performance.

5.1.3. Results and analysis

The best found correct recognition rates (_BstCRR_) with respect to different feature extraction techniques are listed in Table 3. It is well known that CRR is a function of feature number and the best found CRR is the one with the peak value corresponding to the optimal feature number (NOpt) which is obtained by exhaustively searching all possible feature numbers. Table 4 ranks the best found CRRs with rank 1 indicating the best performance while rank 9 indicating the worst performance.

Table 3. Best found CRR (%) for single feature extractors

FE Tech.	No. of subjects in the generic database (SG)									
Empty Cell	60	80	100	150	200	250	300	400	600	800
PCA	64.90	65.17	65.11	65.57	65.74	65.79	65.95	66.46	66.70	67.05
NOpt	101.6	98.3	89.9	82	78.6	74.5	73.1	74.5	65.7	60.9
Bayes	68.79	69.52	69.88	70.77	70.60	70.73	71.07	71.09	71.58	71.82
NOpt	186.8	174.4	179.0	150.1	156.9	151.6	133.1	122.2	116.4	114.6
FLDA	65.41	64.32	62.15	57.90	53.45	49.29	45.39	37.70	26.57	17.93
NOpt	57.4	74.4	91.9	125.8	149.5	171.1	166.9	200.0	241.4	284.7
RLDA0	69.54	71.57	71.69	71.30	69.62	67.65	65.99	61.75	52.97	36.08
NOpt	45.4	60.3	76.7	115.7	154.2	194.6	236.1	316.2	476	636
RLDA?	70.31	72.83	74.14	75.32	75.85	76.06	76.55	76.80	76.98	77.16
NOpt	43.2	59.4	74.6	112.8	150.9	189.2	231.7	310.3	469.7	627.8

RLDA1	62.45	64.18	65.38	66.92	67.84	68.48	69.19	69.34	70.16	70.80
NOpt	40	50.7	70.7	107.5	147.7	187.9	227.4	305.6	465.1	625.2
KPCA	55.11	55.85	56.12	56.74	57.11	57.17	57.28	57.45	57.48	57.55
NOpt	283.3	350.9	400.5	649.2	756.9	723.8	746.8	730.2	830	834.6
GDA	64.77	66.48	66.64	68.78	70.37	71.72	73.45	75.43	78.25	79.93
NOpt	58.0	72.6	77.3	74.8	72.4	65.0	57.5	53.7	44.1	47.2
KDDA	69.99	71.26	71.77	73.50	74.31	74.71	75.62	76.61	77.95	79.48
NOpt	56.6	65.4	67.8	71.1	66.4	58.5	54.6	42.8	31.0	32.2

Table 4. Rank of the best found CRR for single feature extractors

SG	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9
60	RLDA?	KDDA	RLDA0	Bayes	FLDA	PCA	GDA	RLDA1	KPCA
80	RLDA?	RLDA0	KDDA	Bayes	GDA	PCA	FLDA	RLDA1	KPCA
100	RLDA?	KDDA	RLDA0	Bayes	GDA	RLDA1	PCA	FLDA	KPCA
150	RLDA?	KDDA	RLDA0	Bayes	GDA	RLDA1	PCA	FLDA	KPCA
200	RLDA?	KDDA	Bayes	GDA	RLDA0	RLDA1	PCA	KPCA	FLDA
250	RLDA?	KDDA	GDA	Bayes	RLDA1	RLDA0	PCA	KPCA	FLDA
300	RLDA?	KDDA	GDA	Bayes	RLDA1	RLDA0	PCA	KPCA	FLDA
400	RLDA?	KDDA	GDA	Bayes	RLDA1	PCA	RLDA0	KPCA	FLDA
600	KDDA	GDA	RLDA?	Bayes	RLDA1	PCA	KPCA	RLDA0	FLDA
800	GDA	KDDA	RLDA?	Bayes	RLDA1	PCA	KPCA	RLDA0	FLDA

It can be observed that supervised learning techniques outperform those unsupervised ones. The best two approaches are always supervised techniques, i.e., RLDA?/ KDDA/ RLDA0/GDA, regardless of the size of the generic database. In comparing with linear solutions, RLDA? outperforms others if the regularization factor ? is appropriately chosen. IntraBayes solution comes as the second which outperforms FLDA and PCA. As for nonlinear solutions, KDDA is superior to GDA and KPCA with KPCA giving the worst performance. If a large generic database is available (SG?400), KDDA,RLDA? and GDA give the best performance followed by the IntraBayes solution, RLDA1 and PCA while KPCA, RLDA0 and FLDA are the worst, i.e., RLDA??KDDA?GDA>IntraBayes>RLDA1>PCA>KPCA>RLDA0>FLDA. If a small database is available (SG<150), the overall ranks change to RLDA??KDDA?RLDA0>IntraBayes>GDA?PCA>RLDA1>FLDA>KPCA. With a medium sized generic database (150<SG<400), the corresponding ranks become RLDA??KDDA>GDA?IntraBayes>RLDA1?PCA?RLDA0>KPCA>FLDA.

As indicated in Table 3, _BstCRR_ is affected by the size of the generic database used for training. For RLDA1,?, KDDA and GDA, a significant improvement of _BstCRR_ can be observed as more subjects are included. This is due to the fact that the increasing of training samples helps to reduce the variance in the estimation of Sw and Sb. Therefore, the learning capacity of the algorithm increases resulting in a better performance [33]. However, only marginal improvement can be observed for PCA, KPCA and IntraBayes solutions. This can be explained as follows. PCA and KPCA are both unsupervised techniques without considering class label. They produce feature subspaces by maximizing both inter- and intra-subject variations. By increasing training subjects, both inter-subject and intra-subject variations increase. Thus, the extracted feature subspace contains more inter-subject variations which are useful for classification as well as more intra-subject variations which have negative effects. Although learning more inter-subject information will improve the classification performance, such improvement is discounted by retaining more intra-subject variations in the reduced feature subspace due to the nature of unsupervised learning. Therefore, only marginal improvement can be observed. IntraBayes solution performed here is a maximum likelihood version of the standard Bayes method [22] in which only intra-subject variations are considered. With the increasing of training subjects, more intra-subject difference samples are available for training, reducing the variance in the estimation of the intra-subject subspace. Therefore, the recognition performance improved. However, since only intra-subject variations are considered in the IntraBayes method, the performance improvement due to the increasing of inter-subject information cannot be observed. Therefore, only marginal improvement is achieved compared to those LDA based solutions which use both intra- and inter-subject information. While for _FLDA_ and RLDA0, the recognition performance deteriorates as the number of training subjects increases. This can be expected. Both these two methods use the conventional Fisher's criterion, which produces the optimal features by maximizing the ratio of between-class scatter and within-class scatter (Sb/Sw). For _FLDA_ solution [5], the LDA procedure is performed after a PCA feature reduction. Therefore, Sw is estimated in the MFLDA=N-SG dimensional subspace [5]. As for RLDA0 [7], Sb is firstly diagonalized and Sw is estimated in the between-class subspace with the dimensionality of MRLDA0=SG-1. Thus, with the increasing of the number of subjects while keeping the number of samples per subject approximately fixed, both the values of MFLDA and MRLDA0 increase resulting in a higher dimensional Sw estimation. Without losing generality, let us assume the number of samples per subject is same for all subjects, denoted as _C_. Therefore, the number of training samples available to estimate Sw is N=C×SG while the number of elements of Sw matrix to be estimated is (N-SG)2/2=(C-1)2SG2/2 for _FLDA_ and (SG-1)2/2 for RLDA0, respectively (please note that ?/2? is used due to the fact that Sw is a symmetric matrix). Thus the number of elements to be estimated in Sw is of order O(SG2); however, the number of training samples is of order O(SG). This indicates that increasing number of subjects (SG) but constant number of samples per subject (_C_) worsen the SSS problem. This significantly increases the variance in the estimation of Sw [11]. Therefore, a worse recognition performance is observed. This suggests that a regularization scheme to reduce the estimation variance of Sw in LDA based solutions is necessary not only when the number of training samples for each class is small but also under the scenario when the number of classes is large.

The best found CRR can be viewed as a potential recognition capacity which requires a feature selection procedure to achieve the optimal performance. However, systematically determining the optimal feature number NOpt a priori is a difficult task. Therefore, in addition to _BstCRR_ , CRR with all obtained features denoted as _AllCRR_ is also reported. In such a case, a feature selection procedure can be circumvented which is more applicable in practice. In addition, for PCA and IntraBayes solutions, a well known e% energy capturing rule is adopted to determine the feature number, i.e., _N_ features are retained for performance evaluation such that ?i=1N?i/?i=1Nall?i?e%, where Nall is the number of total extracted features and ?i is the ith eigenvalue of the sample covariance matrix sorted in a descending order. Table. 5 lists the CRRs with all extracted features for RLDA0,?,1, FLDA, KDDA, GDA and KPCA as well as the CRRs for PCA and IntraBayes following an e% energy capturing rule where e=[70,80,90,100]. In order to evaluate the disparity between the _BstCRR_ and _AllCRR_ , their difference is also listed, denoted as ?, where ?=BstCRR-AllCRR. It can be observed that ? increases as the size of generic database (number of subjects included) increases except for RLDA0. This is especially true for GDA, PCA and IntraBayes. Fig. 3 depicts the CRR of PCA and IntraBayes with the database size (SG) of 60 and 800 vs number of features. Obviously, monotonic increasing curves can be observed when SG=60; however, when SG=800, _CRR_ decreases rapidly as the feature number increases with the peak CRR achieved if only small percent of features are utilized. This is consistent with our previous consideration that the increasing of the number of generic subjects results in a higher dimensional feature subspace, which leads to a severe overfitting. However, for FLDA, RLDA0,? KPCA and KDDA, such disparity is still small (??5%) even with a large generic database (SG=800).This indicates that the identification with all extracted features is a practical and reasonable choice for these techniques.

Table 5. CRR (%) for single feature extractors with all features

FE Tech.	No. of subjects in the generic database (SG)									
Empty Cell	60	80	100	150	200	250	300	400	600	800
PCA-70%	50.84	52.40	53.35	54.38	55.33	56.24	56.54	57.04	57.28	57.58
80%	58.90	60.92	62.26	63.08	64.12	64.41	64.43	65.09	65.45	65.31
90%	63.96	64.26	64.04	63.13	62.56	61.97	61.37	60.30	58.96	58.44
100%	60.35	57.09	54.37	46.98	39.87	33.04	28.21	20.57	12.35	8.42
?	4.55	7.27	10.74	8.59	25.87	32.75	37.74	45.89	54.35	58.63
Bayes-70%	50.60	53.31	55.64	59.27	61.60	62.86	64.00	65.51	66.36	66.81
80%	59.04	61.91	64.12	66.86	68.37	68.99	69.88	70.45	70.71	70.73
90%	65.26	67.67	68.50	70.03	69.62	69.23	68.89	67.49	65.53	63.50
100%	67.98	67.20	65.71	61.21	56.01	51.74	47.10	36.27	23.27	15.93
?	0.81	2.32	4.17	9.56	14.59	18.99	23.97	34.82	48.31	55.89
FLDA	65.17	64.15	61.82	57.27	52.41	47.75	43.17	35.05	22.55	14.77
?	0.24	0.17	0.33	0.63	1.04	1.54	2.22	2.65	4.02	3.26
RLDA0	69.45	71.36	71.59	71.25	69.48	67.56	65.87	61.66	52.90	36.05
?	0.09	0.21	0.1	0.05	0.14	0.09	0.12	0.09	0.07	0.03
RLDA?	70.09	72.60	73.89	74.95	75.44	75.60	76.01	76.08	76.02	76.15
?	0.22	0.23	0.25	0.37	0.41	0.46	0.54	0.72	0.96	1.01
RLDA1	60.39	61.69	62.51	62.88	63.63	63.76	63.78	63.93	63.92	63.69
?	2.06	2.49	2.87	4.04	4.21	4.72	5.41	5.41	6.24	7.11
KPCA	55.06	55.80	56.07	56.68	56.97	56.90	56.86	56.81	56.72	56.58
?	0.06	0.05	0.05	0.06	0.14	0.27	0.42	0.64	0.76	0.97
GDA	64.68	66.28	65.93	66.44	65.67	64.83	63.80	63.94	65.52	66.46
?	0.09	0.2	0.71	2.34	4.7	6.89	9.65	11.49	12.73	13.47
KDDA	69.85	71.13	71.90	73.22	73.66	73.77	74.45	75.16	75.22	75.39
?	0.14	0.13	0.17	0.28	0.65	0.94	1.17	1.45	2.73	4.09

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Fig. 3. Correct recognition rate of PCA and IntraBayes vs. feature number.

Similarly, the corresponding _AllCRR_ s are ranked in Table 6. For PCA and IntraBayes, CRRs corresponding to 80% energy capturing rule are used for ranking. The comparative ranking of _AllCRR_ is similar to that of _BstCRR_ except that the _AllCRR_ of GDA deviates much from its optima when facing a large generic database, resulting in a rank degradation.

Table 6. Rank of CRR for single feature extractors with all features

SG	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9
60	RLDA?	KDDA	RLDA0	FLDA	GDA	RLDA1	Bayes	PCA	KPCA
80	RLDA?	RLDA0	KDDA	GDA	FLDA	Bayes	RLDA1	PCA	KPCA
100	RLDA?	KDDA	RLDA0	GDA	Bayes	RLDA1	PCA	FLDA	KPCA
150	RLDA?	KDDA	RLDA0	Bayes	GDA	PCA	RLDA1	FLDA	KPCA
200	RLDA?	KDDA	RLDA0	Bayes	GDA	PCA	RLDA1	KPCA	FLDA
250	RLDA?	KDDA	Bayes	RLDA0	GDA	PCA	RLDA1	KPCA	FLDA

300	RLDA?	KDDA	Bayes	RLDA0	PCA	GDA	RLDA1	KPCA	FLDA
400	RLDA?	KDDA	Bayes	PCA	GDA	RLDA1	RLDA0	KPCA	FLDA
600	RLDA?	KDDA	Bayes	GDA	PCA	RLDA1	KPCA	RLDA0	FLDA
800	RLDA?	KDDA	Bayes	GDA	PCA	RLDA1	KPCA	RLDA0	FLDA

The experimental results demonstrate that the generic learning framework with a reasonably sized generic database can provide a satisfying recognition performance under the one training sample scenario. In particular, supervised techniques outperform unsupervised techniques in most cases and nonlinear solutions depict better performance compared to linear solutions as the size of generic database increases.

5.2. Experiment II?generic learning: multiple feature extractors

The goal of this second experiment is to test the hypothesis that a multi-learner framework, operating on a large generic database, achieves better recognition performance compared to that of single recognizer.

5.2.1. Database

The same test set _TstD_ in experiment I is utilized in this experiment with the same gallery and probe configuration. At the same time, a subset of 900 subjects are randomly selected from the remaining 960 subjects to form a large-scale _GenD_. From _GenD_ , _M_ training subsets SGenDi,i=1,?,M, are generated. Each subset contains the image samples of _S_ subjects selected from total 900 subjects in _GenD_ without replacement. In this experiment, _M_ is set to 1?100 and _S_ is varied among [60,80,100,150,200]. The selection of _TstD_ is repeated 10 times and the reported here results are the average of 10 repetitions.

5.2.2. Protocol and setting

In the training session, a feature extractor is applied on each generic subset, resulting in _M_ feature subspaces. All seven different feature extraction techniques applied in experiment I have been performed in this experiment as well. In the test, all gallery images and the probe are projected to these feature subspaces, respectively. In each feature subspace, a single nearest neighbor classifier is applied to determine the probe's identity independently. The final determination is obtained by aggregating the decisions from all classifiers with a sum rule and a majority vote rule. For comparison purposes, the recognition performance of the single recognizer by applying the feature extraction algorithm on the whole _GenD_ is also evaluated.

5.2.3. Results and analysis

The best found CRRs of the multi-learner solution (BstCRRM) as well as the single solution (BstCRRS) with respect to different feature extraction techniques are listed in Table 7. BstCRRM is obtained by exhaustively searching all possible feature numbers for each FR subsystem. In order to save high computational cost, the searching procedure is performed based on the assumption that the feature subspace of each FR subsystem has the same dimensionality. Similar to experiment I, CRRs by using all features are also listed in Table 8, denoted as AllCRRM/AllCRRS.

Table 7. Best found CRR (%) for multiple learner solution (100 FR subsystems) and single solution

FE Tech.	Single FR	No. of subjects in each generic subset (S)									
Empty Cell	900	60	80	100	150	200	60	80	100	150	200
Empty Cell	Empty Cell	Majority vote	Sum rule								
PCA	67.54	69.14	68.86	68.79	68.95	68.98	68.63	68.62	68.67	68.81	68.75
NOpt	77	95.5	82.8	76.6	78.3	72	87.1	83.6	82.8	76.8	69.3

Bayes	72.66	73.62	73.88	73.52	73.57	73.31	73.02	73.33	73.02	73.12	73.18
NOpt	123	183.9	192.7	180.8	175.5	132.3	182	183	163.5	148.4	145.6
FLDA	16.43	80.52	79.48	78.45	75.10	71.77	78.94	78.72	76.39	73.08	68.80
NOpt	88	13	17.2	19	15.7	21.3	8	7	8.9	10.6	10.1
RLDA0	35.54	79.94	79.49	78.48	75.96	73.64	78.74	78.34	77.46	75.27	73.02
NOpt	713	25.3	45.2	65.9	110.1	149.8	22.9	45.1	61.7	109.1	148.9
RLDA?	77.75	79.48	79.59	79.36	78.78	78.26	78.81	79.04	78.94	78.25	78.09
NOpt	713	23	39.1	58.7	101.1	144	21.9	41.3	57.4	101.7	144.7
RLDA1	71.59	79.96	80.28	79.38	79.19	78.74	79.11	79.56	79.46	79.56	78.36
NOpt	705	22.4	40.1	55.4	96.4	139.1	23	38.3	53.7	95.3	136.5
KPCA	60.14	55.23	55.90	56.34	56.78	57.06	55.20	55.90	56.27	56.78	57.02
NOpt	73.5	213.8	239.2	302.9	466.3	610.4	203.1	245	289.1	465	616
GDA	81.39	80.17	81.39	81.73	82.30	82.12	79.05	79.54	80.58	80.54	81.20
NOpt	30	19.1	18.1	16.4	16.9	19.5	11.8	8.8	9.3	13.6	15.1
KDDA	80.81	82.04	82.53	82.61	82.62	82.09	80.63	81.28	81.33	81.55	81.43
NOpt	22	12.8	11.8	13.2	16.5	20.6	9	11.8	12.3	14.3	16.1

Table 8. CRR (%) for multiple learner solution (100 FR subsystems) and single solution with all features

FE Tech.	Single FR	No. of subjects in each generic subset (S)									
Empty Cell	900	60	80	100	150	200	60	80	100	150	200
Empty Cell	Empty Cell	Majority vote					Sum rule				
PCA	7.74	64.00	61.37	57.73	49.59	42.6	63.91	60.93	57.62	49.48	42.34
Bayes	14.10	72.86	71.95	69.75	64.41	60.27	72.30	71.63	69.48	64.38	59.76
FLDA	12.99	76.62	74.38	71.51	65.07	59.14	75.37	73.02	70.40	64.35	58.25
RLDA0	35.29	76.70	77.24	77.39	75.36	73.18	76.51	77.15	76.88	74.70	72.36
RLDA?	76.91	75.90	76.56	76.98	76.98	77.23	76.08	76.74	77.01	76.99	76.79
RLDA1	63.7	65.74	66.44	66.64	66.68	66.83	66.18	66.73	67.36	66.91	67.15
KPCA	58.01	55.04	55.82	56.26	56.70	56.73	55.13	55.82	56.23	56.67	56.73
GDA	67.17	76.38	75.22	73.92	71.70	68.94	75.39	74.24	72.98	70.63	68.32
KDDA	75.39	77.35	77.43	77.34	77.53	76.97	76.97	77.31	77.22	76.86	76.70

It is evident in Table 7 that the multi-learner solution outperforms the single solution except for _KPCA_. In particular, for FLDA and RLDA0 which are failed with a large-scale database, the improvement by introducing a multi-learner framework is considerable. Comparing BstCRRM and BstCRRS when S=60,M=100 and majority vote scheme is used, obvious improvement can be observed. For FLDA, RLDA0 and RLDA1, more than 8% CRR improvement is achieved. While for other approaches, such improvement ranges between 1% and 2% except for KPCA and GDA. When comparing _AllCRR_ , as indicated in Table 8, the advantage of applying a multi-learner framework is more obvious. For PCA, IntraBayes and GDA, whose _AllCRR_ deviate much from their corresponding optima when facing a large-scale database, the performance improvement is considerable with the CRR enhancement of 66.26%,58.76% and 9.19%, respectively. In addition, it can be observed that there is no significant difference between the two combination schemes with majority vote rule slightly better than sum rule.

Comparing BstCRRM/AllCRRM with respect to different subject number in each generic subset, it can be observed that increasing the size of each generic subset does not necessarily result in an obvious CRR enhancement although the learning capacity of each base leaner may increase as demonstrated in Tables 3 and 5. The improvement of BstCRRM/AllCRRM when S=200 with respect to that of S=60 is less than 2%, some are even negative. However, the computational cost is tripled. In addition, Fig. 4 depicts the relationship between BstCRRM/AllCRRM and the number of subsets (_M_). It can be observed that the CRRs increase rapidly at the initial stage, where M<20; however, such improvement becomes less obvious as more base learners are included. These phenomena can be expected. It is well known that a necessary and sufficient condition for combining a set of learners to be more accurate than any of its individual members is if these base learners are accurate and diverse [47]. Since the number of the total generic subjects is fixed, continuing increasing the number of learners (training subsets) or number of subjects in each subset leads to heavier overlapping between different subsets, thereafter, the base learners trained on which become more similar. The decreasing of base learners? diversity prevents the continuous performance improvement.

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Fig. 4. Best found CRR (BstCRR) and CRR with all features (_AllCRR_) vs. number of base learners; each base learner is trained on a generic subset containing 60 subjects; upper: PCA, IntraBayes, FLDA; middle: RLDA0, RLDA?, RLDA1; bottom: KPCA, KDDA, GDA.

The results suggest that the proposed multi-learner framework improves the recognition performance when a large-scale generic database is available. In addition to the performance improvement, the multi-learner framework allows for distributed execution of the computational load on clusters or networks of precessing units. This is especially useful if the generic database is large since the corresponding computational cost and the memory requirement to train a single global FR system are immense.

5.3. Experiment III?specific learning

In order to verify the effectiveness of the proposed framework, a set of experiments within the specific learning framework are performed in this section. In contrast to generic learning, experiments reported previously the so-called specific learning assumes that the recognition engine will be trained on image samples coming from the subjects of interest, for example, gallery samples (one frontal image for each subject) in our case. Therefore only _TstD_ is used in the experiment which is the same as that in experiments I and II. As before, the results reported here are the average of 10 repetitions to eliminate random variations in the experiment.

Three state-of-the-art learning solutions capable of dealing with the one training sample problem are adopted. Namely, E(PC)2A1+/A2+ [13], SPCA [14] and SOM [15] are utilized. The parameters in these algorithms are set to the values suggested by the corresponding authors. In addition, PCA approach trained on the gallery samples is also performed as a baseline.

Table 9 lists the best found CRRs of PCA, E(PC)2A1+/A2+, SPCA and SOM. For

PCA, E(PC)2A1+/A2+ and SPCA, the best CRRs are the peak value with the optimal feature number Nopt which is obtained by searching all possible feature numbers. While for SOM, the best CRR is obtained by searching all possible _k_ values, a parameter of _k_ NN ensemble defined in Ref. [15].

Table 9. Best found CRR (%) for specific learning

Empty Cell	PCA	E(PC)2A1+	E(PC)2A2+	SPCA	SOM
	66.00	59.59	54.16	64.13	58.75
Nopt/k*	58	55	59	59	60

Surprisingly enough, in the experiments performed here, the standard PCA achieves the best recognition rate. This suggests that although the state-of-the-art specific approaches such as E(PC)2A1+/A2+, SPCA and SOM demonstrate satisfying performance in frontal face recognition tasks where small variations are considered [13], [14], [15], their performance under realistic applications with considerable pose, aging variations is still in question. Comparing the recognition performance of specific solutions vs. generic solutions, it is easy to see that within the generic framework, available FR modules such as IntraBayes, RLDA, KDDA and GDA outperform specific approaches if a reasonably sized generic database is available for training.

In the above sets of experiments, we discussed issues pertinent to the application of the generic learning framework to the one training sample per subject face recognition problem. Some of our findings are highlighted in the following:

* ?

Generic learning framework should be viewed as a reasonable solution to the one training sample problem. Available appearance-based face recognition algorithms can be readily embedded into the framework. Compared to specific learning, where the training samples are limited to those corresponding subjects of interest, generic learning demonstrates the better generalization performance due to the fact that the estimation of the face pattern distribution is performed on a much larger generic database which contains more discriminatory information. Increased estimation accuracy leads to better recognition performance.

* ?

In general, supervised solutions (LDA-based) exhibit better recognition performance compared to unsupervised solutions when used within generic learning framework. In addition, nonlinear approaches are superior to those linear ones when facing a large generic database which contains more complex data distribution. This is consistent with the results reported in traditional FR scenarios, where at least two training samples are available for each subject and same subjects are present in both training and testing sets.

* ?

Performance of FLDA and RLDA0 deteriorates rapidly when used in conjunction with a large training database. This indicates that the supervised techniques are subjectable to the SSS problem not only under the traditional scenario where the number of the training samples for each class is small but also when the number of classes is large. Therefore, a regularization step is also necessary for supervised solutions if large number of classes are considered.

* ?

Multi-learner framework is an efficient and cost-effective strategy to boost the recognition performance when a large generic database is available. In particular: (1) trained on a smaller data set, techniques such as FLDA and RLDA0 are less subjectable to the SSS problem, resulting in better performance. It can be easily observed that the performance of FLDA and RLDA0 within the multi-learner framework is even better than that of a stand-alone RLDA?, a regularized solution with a fine tuned regularization parameter. This indicates that a determination-of-regularization-parameter procedure can be circumvented. (2) A multi-learner solution can alleviate overfitting. This is especially useful when the multi-learner is invoked to boost the performance of techniques such as PCA, IntraBayes and GDA. As it was shown, the recognition performance of such methods when all extracted features are used is inferior to the performance obtained using a smaller ?optimal? feature set, the determination on which, however, requires feature selection in real applications. Using the multi-learner framework, feature selection can be avoided. (3) From a computational complexity point of view, the method is efficient, since the FR subtasks can be processed in parallel and the computation cost can be distributed to different work stations.

6\. Conclusion

In this paper, the so-called generic learning framework was introduced to address the one training sample face recognition problem. An FR system is trained on a generic database which then could be applied to a specific FR task. The generic database is built off-line using images from subjects other than those to be identified during actual applications. Extensive experimentation has been performed to determine the recognition performance of many state-of-the-art FR algorithms within the generic learning framework. In addition, a multi-learner framework is proposed to further boost the recognition performance. Experimentation results suggest that, under the one training sample scenario, generic learning solutions are superior to those specific learning solutions and the combination of a set of local simpler solutions outperforms a global solution in terms of recognition performance as well as the computation efficiency.

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