J. Vis. Commun. Image R. 32 (2015) 170–179

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Classification schemes based on Partial Least Squares for face identification ☆

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ARTICLE INFO

Article history:
Received 15 July 2014
Accepted 4 August 2015
Available online 8 August 2015

Keywords:
Face identification
Partial Least Squares
One-against-none
One-against-all
One-against-some
Scalable face recognition
Classification schemes
Gallery enrollment

ABSTRACT

Approaches based on the construction of highly discriminative models, such as one-against-all classification schemes, have been employed successfully in face identification. However, their main drawback is the reduction in the scalability once the models for each individual depend on the remaining subjects. Therefore, when new subjects are enrolled, it is necessary to rebuild all models to take into account the new individuals. This work addresses different classification schemes based on Partial Least Squares employed to face identification. First, the one-against-all and the one-against-some classification schemes are described and, based on their drawbacks, a classification scheme referred to as one-against-none is proposed. This novel approach considers face samples that do not belong to subjects in the gallery. Experimental results show that it achieves similar results to the one-against-all and one-against-some even though it does not depend on the remaining subjects in the gallery to build the models.

1. Introduction

Face recognition is a very active research topic due to its applications in areas such as surveillance, biometrics and human computer interaction. Face verification and identification figure among the main tasks performed by face recognition. While the former is responsible for accepting or denying the identity claimed by an individual given a pair of samples, the latter focuses on matching a sample of an unknown person to a gallery of known subjects.

The identification task presents particular interest in surveillance applications that perform face recognition in monitored areas, in which the identity of individuals needs to be determined to provide, for example, non-intrusive monitoring of circulation on restricted areas. Due to the dynamic nature of these environments, in which new subjects are incrementally added, the identification system not only needs to be accurate, but also it is important to provide efficient and robust enrollment mechanisms.

Due to its ability of generating discriminative subspaces and working with few high dimensional input samples, the statistical method *Partial Least Squares* (PLS) [1] has been successfully applied to the problem of face recognition in the past few years for both verification and identification tasks [2–7]. These works employ the one-against-all classification scheme combined with PLS, which provides high recognition rates for the identification task [2,4,6]. However, this classification scheme presents the drawback of not being scalable to the enrollment of new subjects since all existing PLS models representing the subjects in the gallery need to be rebuilt, leading to a high computational cost proportional to the gallery size.

To handle the enrollment of new subjects to the gallery while maintaining the generation of highly discriminative subspaces with PLS, we have recently proposed a classification scheme, called one-against-some [8], which does not consider all remaining subjects as counterexamples, but only a subset of them. The one-against-some approach maintains a trade-off between the discriminatory power achieved by the one-against-all, in which all remaining subjects are set as counterexamples, and allows scalability when new subjects are enrolled in the gallery since the PLS models used to represent subjects already enrolled do not need to be rebuilt. However, as a drawback, the number of PLS models that have to be built is larger than the number required by the one-against-all approach and a priority queue is employed to maintain a low number of projections when a probe sample is presented to the system.

In this work, we propose a novel classification scheme based on PLS models, called *one-against-none*, which does not require the addition of samples of the remaining subjects as counterexamples,

☆ This paper has been recommended for acceptance by Prof. M.T. Sun.

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http://dx.doi.org/10.1016/j.jvcir.2015.08.005
1047-3203/

but only the addition of fixed set of samples that are not required to belong to any subject under consideration. These samples, which do not have intersection with the subject being considered, are referred to as extra samples. When employing the one-against-none classification scheme, the number of PLS models to be built is equal to the number of the subjects, which maintains a low number of projections. In this work, we also evaluate different approaches to choosing the counterexamples in the one-against-some classification scheme.

In the experiments, we conduct an evaluation of the three classification schemes based on PLS: one-against-all, one-against-some and one-against-none, emphasizing their strong and weak points regarding computational cost, memory consumption and accuracy.

2. Related work

A brief review and discussion of concepts and references related to face recognition, feature descriptors and classification schemes are included in this section.

2.1. Face recognition

Face recognition has been extensively investigated for decades and is still a challenging problem. Although various approaches have achieved high recognition accuracy rates under specific conditions, several factors can affect their performance such as varying pose, non-uniform illumination, partial occlusion, scalability, facial characteristics, and other uncontrolled conditions.

A face recognition system usually consists of four main components: face detection, alignment, feature extraction, and matching. Some comprehensive surveys on face recognition are available in the literature [9,10].

Techniques for face recognition are commonly classified into two main categories, local and holistic approaches. Local approaches [11–14] extract facial features, such as nose, eyes and mouth, to discriminate faces based on combination and evaluation of local statistics, whereas holistic approaches [15–18] capture information from the entire face image to perform the recognition.

Since the recognition problem can involve a large number of individuals in a gallery, scalability is an important issue in face identification systems. Therefore, search techniques employed to match probe samples in the gallery must be efficient [19,20]. Additionally, the model reconstruction whenever a new individual is added to the gallery can significantly affect the system performance.

In [21], the authors propose a regularization method of learning a similarity metric for unconstrained face verification. A learning objective function is formulated by considering the discrimination for separating among dissimilar image-pairs and the robustness to the large intrapersonal variations. The performance of their method is evaluated on the Labeled Faces in the Wild (LFW) data set. The work in [22] proposes an unconstrained correlation filter applied to the face recognition problem to extract discriminative features in class-dependence feature analysis (CFA). Experiments are conducted on five data sets (AR, FERET, FRGC, LFW, CAS-PEAL-R1). In [23], the authors propose a correlation filter bank for face recognition, which explores local features and the combination of different face subregions. Experimental results are evaluated on public data sets (FERET, LFW, CAS-PEAL-R1).

Some methods project face images onto a lower dimensional space to reduce data high-dimensionality, such as Eigenface [24], Fisherface [25], Tensorface [26] and Bayesian algorithms [27]. Thus, face variations can be modeled under different illumination conditions through a training face set, where new face samples can be projected onto low dimensional spaces and compared to a number of images. Face recognition methods based on Partial Least Squares (PLS) has recently provided interesting results [2–8].

2.2. Feature descriptors

Facial features, such as eyes, nose, mouth and eyebrows, can be extracted by edge-based detectors. However, a common problem with these approaches is that features can be affected by noise, illumination and occlusion. Therefore, several local feature descriptors have been employed effectively in face description. There are three main approaches, based on texture information to capture local patterns in the face [28–30,13], shape [31,32,15,14], and color information [13,16,33,34].

Fusion of descriptors has been explored for face recognition [35,36], where complementary local and global features extracted from regions and the entire image, respectively, are combined to form a feature vector. To avoid the need for selecting the local descriptors, deep learning approaches have been employed on face recognition so that robust local descriptors can be learned automatically [17].

2.3. Classification schemes

Some classification strategies can be used in the matching of a probe sample against a face gallery, such as the one-against-all scheme [37,38], where all training models must be reconstructed when a new subject s_i is presented to the system, since all the remaining samples are employed as counterexamples (negative class) for s_i. Even though this strategy can achieve high recognition rates, it requires high training time.

Pairwise classification [39,40] converts multi-class problems into a series of two-class (binary) problems. Differently from the one-against-all scheme, which constructs one binary classifier for each class c_i such that positive training samples belong to class c_i and negative training samples are formed by all remaining classes, the pairwise classification converts an n-class problem into $n(n-1)/2$ binary problems, one for each pair of classes.

One-against-some scheme [8,41] has been proposed for the person re-identification problem, where only a subset of subjects are considered as negative samples, instead of all remaining individuals as in the one-against-all scheme. Thus, not all individuals need to be known for the enrollment of a new subject, avoiding the reconstruction of the existing gallery models to handle the new individual.

3. Classification schemes based on partial least squares

In this section, we present the classification schemes based on Partial Least Squares which have been employed to the face identification problem. We describe two previously proposed approaches: the *one-against-all* classification scheme [2] and the *one-against-some* classification scheme [8]. In addition, based on their drawbacks regarding the enrollment of new subjects, we propose the classification scheme called *one-against-none*.

The face identification approaches based on subject modeling and Partial Least Squares are structured in three main blocks: feature extraction, individual modeling for subjects in the gallery and execution of regressions to perform the matching of probe samples to subjects in the gallery. The general approach is illustrated in Fig. 1 and each of its parts is described in details in Sections 3.1–3.4, pointing out the differences among the three