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Semi-supervised local ridge regression for local matching based face recognition

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ABSTRACT

In this paper, a novel algorithm named Semi-supervised Local Ridge Regression (SSLRR) is proposed for local matching based face recognition. Compared with other algorithms, the proposed algorithm possesses two advantages. Firstly, SSLRR utilizes a multiple graph based semi-supervised technique to propagate the class labels of labeled samples to the unlabeled ones. Thus, the information of both labeled and unlabeled data can be employed in our algorithm to improve its performance. Secondly, unlike most local matching based face recognition algorithms which assume different sub-images from the same face are independent, an adaptive non-negative weight vector is introduced into our SSLRR to combine the Laplacian matrices obtained by different sub-images. Therefore, the latent complementary information of multiple sub-patterns from the same face image can be taken into account. Moreover, a simple yet efficient iterative update scheme is also proposed to solve our SSLRR model. Extensive experiments are performed on five standard face databases (Yale, Extended YaleB, AR, CMU PIE and LFW) to demonstrate the efficiency of the proposed algorithm. Experimental results show that SSLRR obtains better recognition performance than some other state-of-the-art approaches.

1. Introduction

Face recognition is one of the classical problems in pattern recognition and biometric fields. Though the robustness and accuracy of face recognition systems have been greatly improved in recent years [1–4], the face recognition problem is still a complex and challenging task. This is because the appearances of face features are always affected by many factors such as illumination, expression, pose and disguise.

Nowadays, a large number of researchers have proposed various methods for face recognition. According to some studies [1–4,18,19], these methods can be roughly classified into two categories: holistic matching based methods and local matching based methods. Holistic matching based methods, which use the whole face region as raw input to the recognition system, have been extensively studied. In most holistic based face recognition approaches, a subspace is first constructed using some feature extraction or dimensionality reduction techniques to avoid the curse of dimensionality. Then, the face images are projected into the low-dimensional subspace for classification and recognition [3]. Currently, the most representative and popular algorithms employed for holistic matching based face recognition are Principal Component Analysis (PCA) [5], Linear Discriminant Analysis (LDA) [6], Independent Component Analysis (ICA) [7], Non-negative Matrix Factorization (NMF) [8], Isometric Feature Mapping (Isomap) [9], Locally Linear Embedding (LLE) [10], Locality Preserving Projections (LPP) [11], Marginal Fisher Analysis (MFA) [12] and so on.

Despite their wide applications in face recognition, the performances of the holistic matching based methods may be affected by the variations in head pose, lighting condition, and facial expression in real-world face images [3]. Therefore, many local matching based face recognition algorithms have been developed based on the observation that some local facial features of an individual do not vary with the head pose, lighting condition and facial expression changes [3,13]. The general idea of local matching based methods is to first partition the face images into several smaller local patches and then classify the face images by comparing and combining the corresponding local features. According to whether the labels of face images are employed during the training procedure, the local matching based methods can be subdivided into two groups: unsupervised and supervised. Though the unsupervised local matching based face recognition algorithms, such as Modular PCA (ModPCA) [14], Sub-pattern based PCA (SpPCA)

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[15] and Structure-Preserved Projection (SPP) [16], achieved better recognition results than the holistic matching based face recognition algorithms, a main drawback of them is that they ignore the class information of training data, which may weaken their recognition performance. In order to overcome this limitation, some supervised local matching based face recognition approaches have been proposed. Local Ridge Regression (LRR) [17] is a typical supervised approach which incorporates the label information of training samples into the local matching based face recognition task. In LRR, the whole face images are firstly partitioned into a set of equally sized local regions. Then, Ridge Regression (RR) [18], which is a regularized least square method, is performed on the local regions sharing the same original face component to train the corresponding classifier. Beside LRR, some other supervised local algorithms such as S-SPP [16], Aw-SpPCA [19], Aw-SpLPP [20], and SS-SPP [21] have also been proposed and showed promising face recognition performances.

Though the experimental results indicated that the supervised local matching based face recognition algorithms outperformed unsupervised ones, these algorithms demand that the input training face images are completely labeled [22], which may prevent their application in some cases. Since labeling all the training face images often requires expensive human labor, the cost associated with the labeling process may render a fully labeled training dataset very time-consuming and infeasible. On the contrary, unlabeled face samples are abundant and can be easily obtained in the real world. Thus, many semi-supervised learning algorithms which incorporate both partially labeled data and abundantly unlabeled data into the learning procedure have been proposed [23]. Among these algorithms, the graph based semi-supervised learning methods are well studied [24–29]. In graph based semi-supervised methods, a weighted undirected graph in which each node represents a data point and the weight of each edge reflects the similarity between data points is first constructed. Then, various strategies are adopted in different methods to take advantage of the graph. In Gaussian Fields and Harmonic Functions (GFHF) [24] and Local and Global Consistency (LGC) [25] algorithms, the researchers assumed that the nearby data points connected in the graph should share similar labels. Thus, they estimated the labels of unlabeled data points by propagating the information of labeled data points over the graph. In some semi-supervised subspace learning methods such as Discriminat Analysis (SDA) [26] and Laplacian regularized Least Square (LapRLS) [27], the constructed graph is utilized to find an optimal low-dimensional subspace in which the geometric structure of both labeled and unlabeled data can be well preserved. Recently, some hybrid semi-supervised algorithms which combine graph based label propagation and subspace learning into a unified framework have also been proposed [28–30]. Although the aforementioned semi-supervised methods have yielded competitive performances in face recognition tasks, they all utilized the holistic information of the face images as input data and belong to the holistic matching based methods. Thus, as we have discussed earlier, their performances may be affected by some problematic factors (e.g., illumination, expression and pose variances) in real-world face images [31]. As a solution to overcome this shortcoming, one can simply incorporates these methods into the local matching based face recognition framework by directly applying them to the sub-pattern sets partitioned from the face images. Nevertheless, a main drawback of this strategy is that it neglects the latent complementary information of the multiple sub-images from the same face, which is crucial to improve the recognition performance [31].

In order to overcome the limitations of existing algorithms, a novel algorithm called Semi-supervised Local Ridge Regression (SSLRR) is proposed in this paper. Firstly, our SSLRR is a semi-supervised local matching based face recognition algorithm. Thus, it can handle the training dataset contains both labeled and unlabeled samples, which makes our SSLRR more flexible than other supervised and unsupervised local matching based face recognition algorithms. In our SSLRR, the labels of the labeled training samples are propagated to the unlabeled samples by a multiple graph based technique so that the information of the unlabeled data samples can be utilized to train the classifiers. Secondly, in the local matching-based face recognition framework, each subimage of a face can be regarded as a sub-pattern contains a partial feature of the face image. Different sub-images divided from the same image can reflect various information of the face image, and have some latent connections with each other since they jointly provide the full information of the whole face. Therefore, for the sake of taking the complementary information of different subpatterns from the same face into account, a non-negative weight vector is introduced into our algorithm to combine the Laplacian matrices obtained from different sub-pattern sets and an adaptive strategy is provided to optimize the elements in the vector. Furthermore, a simple yet efficient iterative update algorithm is also proposed to solve our SSLRR. To the best of our knowledge, SSLRR is the first algorithm which incorporates the semi-supervised learning technique into the local matching based face recognition framework and considers the relationships among various sub-patterns simultaneously. Thus, as can be seen from the experimental results on five benchmark face images databases (Yale, Extended YaleB, AR, CMU PIE and LFW), the recognition performance of the proposed SSLRR is significantly better than other algorithms.

The rest of this paper is organized as follows. In Section 2, we briefly review several approaches that motivate our algorithm. In Section 3, the proposed SSLRR is introduced. Section 4 presents the experimental results on five face databases, and the conclusions are given in Section 5.

2. Related works

In this section, we will briefly review the works related to the proposed SSLRR approach.

2.1. Local ridge regression (LRR)

Local Ridge Regression (LRR) [17] is a local matching based face recognition algorithm which considers the label information of the input face images.

Let $X=\{x_1,x_2,\dots,x_n\}$ denotes n face images belonging to c classes in the training set, $Y=[y_1,y_2,\dots,y_n]^T\in\mathfrak{R}^{n\times c}$ is the class labels and the size of each image is $H_1\times H_2$. In LRR algorithm, each image is first divided into M equally sized sub-images in an overlapping or non-overlapping way. Then, each sub-image is further concatenated into a column vector with the dimensionality of $\bar{d}=H_1\times H_2/M$. Finally, the vectors at the same position of all face images are collected to form a sub-pattern set. For more details about the face image partition process, the readers can refer to Section 3.1 or Ref. [17].

After obtaining M sub-pattern sets, the Ridge Regression (RR) [18] is performed on each sub-pattern set to train M different classifiers as follows:

$$\min_{W^m\in\mathfrak{R}^{\bar{d}\times c}}\|Y-X^{m^T}W^m\|_2^2+\lambda\|W^m\|_2^2,\quad m=1,2,\dots,M \tag{1}$$

where$X^m=[x_1^m,x_2^m,\dots,x_n^m]$ is the sub-pattern set contains the mth sub-pattern of all n training face images, W^m is a matrix to model the linear dependency between the sub-patterns and their labels, and λ is a regularization parameter. The optimal W^m in Eq. (1) can