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Two-phase linear reconstruction measure-based classification for face recognition

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ABSTRACT

In this article we propose several two-phase representation-based classification (RBC) methods that are inspired by the idea of the two-phase test sample sparse representation (TPTSR) method with L_2-norm. We first introduce two simple extensions of TPTSR using L_1-norm alone and the combination of L_1-norm and L_2-norm, respectively. We then propose two-phase linear reconstruction measure-based classification (TPLRMC) by adopting the linear reconstruction measure (LRM). Decomposing each feature sample as a weighted linear combination of the other feature samples, TPLRMC can measure the similarities between any pairs of feature samples. The linear reconstruction coefficients can capture the feature's neighborhood structure that is hidden in data. Thus, these coefficients with L_p-norm regularization can be used as good similarity measures between samples and the test ones in classifier design of TPLRMC to enhance discriminative capability. In regard to the classification procedure, TPLRMC first coarsely searches K nearest neighbors for a given query sample with LRM, then finely represents the query sample as a linear combination of the chosen K nearest neighbors, and finally uses LRM to perform classification. The experimental results on six face recognition databases and two object recognition databases demonstrate that the proposed methods outperform the competitors used in the experiments.

1. Introduction

Face recognition has so far been one of the challenging research areas in both computer vision and machine learning. In a face recognition system, image samples collected from the same face are often varied under complex situations, such as different illuminations, facial expressions, poses and occlusions [39,40]. In face recognition, it is challenging but crucial to robustly represent and accurately classify a query face image. To handle this challenge, the representation-based classification (RBC) methods have been attracted much attention in face recognition [28,50]. In the RBC framework, how the similarity between a query sample and each individual class is accurately calculated plays an important role in represent-

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ing and classifying the query sample [40]. Currently, many methods have been proposed in the vein of RBC, such as in [4,33,35,46].

Roughly speaking, the RBC methods can be divided into three categories: L_1-norm-based representation [4,16,33–35,38,46,47], L_2-norm-based representation [3,20,21,32,39,40,42,43,45,50] and $L_{2,1}$-norm-based representation [24,25,30,31,36]. In the L_1-norm-based representation methods, the representation coefficients are regularized with L_1-norm. One simple but representative method in this vein could be the sparse representation-based classification (SRC) [33,34]. SRC uses a sparse linear combination of training samples to represent the query sample and classifies the query sample according to the class-specific reconstruction residual. To enhance the discriminative power of sparsity, an adaptive sparse representation-based classification (ASRC) method was proposed in [35] for face recognition, which jointly considers correlation and sparsity of data. Unlike both SRC and ASRC that use all the training samples as the dictionary in sparse representation, the sparse representation-based Fisher Discrimination dictionary learning (FDDL) [47] takes into account the discriminative information from both the representation coefficients and the representation residuals in dictionary learning. FDDL performs quite well in image classification. To improve the performance of dictionary learning, a robust and reliable dictionary learning method was proposed in [41] for sample diversity and representation effectiveness in face recognition.

The methods in the second category use L_2-norm to regularize the representation coefficients in learning, instead of L_1-norm. It has also been proven that these methods can construct a fairly accurate representation for a query sample and perform quite well in classification tasks of pattern recognition. The main characteristic of the L_2-norm-based methods is that the L_2-norm regularization offers a closed form solution to the representation coefficients and gives a stable and robust coefficient estimation. It can enhance the stability of the performance on singular problems and give good discrimination in classification [14,50,52]. A typical L_2-norm-based representation method is the collaborative representation-based classification (CRC) [50]. The CRC method makes use of the collaboration between classes to represent the query sample so that the classification performance can be further improved. Inspired by CRC, many new L_2-norm-based representation methods [3,21,32,43,45] have been proposed in the literature. For instance, the two-phase test sample sparse representation (TPTSR) method uses two-phase L_2-norm-based representation [43]. TPTSR uses all the training samples to choose the representative neighbors for each query sample in the first phase, and then uses the chosen neighbors to represent and classify the query samples in the second phase. The two-phase classification framework used in TPTSR has been used in some other approaches, *e.g.*, [7,15,17,39,40,42]. Besides, the linear regression classification (LRC) [20] is another classical L_2-norm-based representation classification method that uses a linear combination of class-specific training samples to represent and classify a query sample. The linear regression model [5,26] has been used in CRC, TPTSR and LRC methods.

In the $L_{2,1}$-norm-based representation, representation coefficients are constrained by a $L_{2,1}$-norm regularization term. $L_{2,1}$-norm-based representation forces the representation coefficients to concentrate on a few classes in order to further improve the pattern discrimination [24,25,30,31,36]. The classification methods using this representation are robust to outliers or large variation in the data distribution [24,25]. Meanwhile, $L_{2,1}$-norm regularization can also be used for dimensionality reduction with robust classification performance [30,31,36]. In addition to the three types of representation-based classification methods, a classification method that combines L_1-norm and L_2-norm-based representation was proposed in [52]. It has been shown that most entries in the representation residuals with the L_1-norm are zeros and a few are relatively large, and the representation residuals with the L_2-norm can contain many small entries but few large ones, so that the L_1-norm can be used for sparseness and the L_2-norm for overcoming outliers, which are both favorable for accurate classification [6,27,52].

In many representation-based classification methods, the representation coefficients are often involved in computing the similarities between samples [1,2,8,11–13,22,23,37,44,49,51]. On the one hand, using the coefficients in computing the similarity measure has been directly adopted in classifier design [2,13,49]. For example, the linear reconstruction measure steered nearest neighbor classification (LRMNN) uses either the L_1-norm or L_2-norm-based representation coefficients as linear reconstruction measure (LRM) to determine the nearest neighbors of a query sample in [49]. Note that the representation coefficients in LRM are also called the linear reconstruction coefficients. The sparsity induced similarity measure proposed in [2] uses L_1-norm-based representation coefficients as a similarity measure for label propagation and action recognition. Using L_1-norm-based coefficients, the sparse coefficient-based k-nearest neighbor classification was proposed in [19]. In [13], sum of L_1-norm-based representation coefficients, called sum of coefficients (SoC), is used as the classification decision rule. Moreover, sparse coding in [12,37,51] also implies that similar samples should be encoded with similar sparse representation coefficients. On the other hand, the representation coefficients as weights among samples are used for automatic graph construction of a given dataset [1,8,11,22,23,44]. Since the representation coefficients can preserve some intrinsic geometric properties of the original high dimensional data and potential discrimination information, the representation-based graph construction has been applied to dimensionality reduction. These representation-based dimensionality reduction methods can be unified into the framework of graph embedding in general [48]. Recently, a nonnegative sparse graph learning method [9] for linear regression includes both label prediction and projection learning and provides a new perspective for graph-based learning. Thus, the representation coefficients can be well applied to pattern classification.

Although the representation-based classification methods perform well in many practical face recognition tasks, their classification performance can be significantly influenced by the variations of face images [39,40]. In this paper, we propose several two-phase RBC methods for improving the classification performance of face recognition. Inspired by the idea of TPTSR using the L_2-norm, we first introduce two extensions of TPTSR, *i.e.*, one is regularized by the L_1-norm and the other one is regularized by combining the L_1-norm and L_2-norm; and then elaborate the proposed two-phase linear reconstruction