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Local graph embedding based on maximum margin criterion via Fuzzy Set

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Abstract

Recently, many algorithms based on locally graph embedding are proposed for dimensional reduction in nonlinear data. However, these algorithms are not effective when dealing with face images affected by variations in illumination conditions, poses or perspectives and different facial expressions. So, distant data points are not deemphasized efficiently by locally graph embedding algorithms and it may degrade the performance of classification. In order to solve the aforementioned problem, this paper proposes a new efficient dimension reduction method—local graph embedding method based on maximum margin criterion via Fuzzy Set for face recognition. Firstly, the goal of this algorithm is preserved under nearest neighbor premise by constructing the fuzzy intrinsic graph and the fuzzy penalty graph. Secondly, two novel fuzzy Laplacian scatter matrices are calculated using Fuzzy K-Nearest Neighbor (FKNN) in the proposed method. Finally, Maximum Margin Criterion (MMC) is used to avoid the "small size sample" problem. The results of face recognition experiments on the ORL, YALE and AR face databases demonstrate the effectiveness of our proposed method.

Keywords: Locally linear embedding (LLE); Dimension reduction; Face recognition; Maximum margin criterion; Local graph embedding

1. Introduction

Many locality preserving-based algorithms have been active areas of research because of their potential applications in computer vision, machine learning and pattern recognition fields.

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Among them, methods include locally linear embedding (LLE) [1,2], isometric feature mapping (ISOMAP) [3], local tangent space alignment (LTSA) [4] and Laplacian eigenmap (LE) [5,6] are widely used. LLE is a linear subspace learning method, which constitutes local coordinates with the least constructed cost and maps them to a global one. Neighborhood preserving embedding (NPE) [7] optimally preserves the local neighborhood reconstruction relationships to find a low-dimensional embedding on the original data manifold. Locality preserving projections (LPP) [8,9] can find an embedding space that preserves local information, which is derived from Laplacian Eigenmap. Recently, Yan et al. [10] proposed linear graph embedding framework (LGE) to unite above manifold learning algorithms. Wan et al. [11] proposed LGE/MMC to solve small size sample problem in LGE algorithms.

However, LGE and LGE/MMC methods can not solve different facial expressions and variations in illumination conditions of face images in the real world. At the same time, distant points are not deemphasized efficiently by LGE and LGE/MMC and it may degrade the performance of classification. How can we completely represent the distribution of these samples and improve classification performance through extracting discriminative information from these samples? Obviously, fuzzy set theory is a good choice. The fuzzy neighbor membership degree can efficiently handle the vagueness and ambiguity of samples being degraded by poor illumination, facial expression variations and distant points. In other words, the fuzzy neighbor membership degree helps to pull the near neighbor samples in same class nearer and nearer and repel the far neighbor samples of different classes farther and farther. So, the novel fuzzy neighbor graphs based on the fuzzy neighbor membership degree can better characterize the compactness and separability.

Many studies have been carried out for fuzzy image filtering, fuzzy image segmentation and fuzzy edge detection by taking advantage of the technology of fuzzy sets [12] in many problems of pattern recognition and image processing [13–16]. To solve these problems, in this paper we investigate local graph embedding method based on maximum margin criterion [17] and the fuzzy set theory for dimensional reduction.

The novelties of our method come from the following perspectives:

1. The proposed method constructs two new fuzzy graphs using FKNN, where it is important to maintain the original neighbor relations for neighboring data points of the same class and also crucial to keep away neighboring data points of different classes. So, the novel fuzzy neighbor graphs based on the fuzzy neighbor membership degree can better characterize the compactness and separability.
2. Through the fuzzy neighbor graphs, the proposed algorithm has lower sensitivities to the sample variations caused by varying illumination, facial expression variations and distant points. So, the class of a new test point can be more reliably predicted by the nearest neighbor criterion, owing to the locally discriminating nature.
3. The proposed method avoids the small sample size problem since it does not need to compute any matrix inversion; therefore, much computational time would be saved for feature extraction. However, the proposed method needs a few CPU time more than LPP and LLE. It is because that the proposed method builds two fuzzy graphs.

The rest of this paper is organized as follows: We review the ideas of several methods in section 2. In Section 3, we propose the idea of the proposed algorithm in detail. In section 4, we introduce the connections between LLE, NPE and the proposed algorithm. Experiments are presented to demonstrate the effectiveness of the proposed algorithm on face recognition in section 5. Finally, we give concluding remarks and a discussion of future work in Section 6.

2. Outlines of FKNN, LPP and MMC

In this section, we briefly review some basic subspace algorithm. Let us consider linear transformation mapping the set of N samples $X = \{x_1, x_2, \dots, x_N\}$, $x_i \in R^D$ into a d-dimensional feature space $Y = \{y_1, y_2, \dots, y_N\}$, where $y_i \in R^d$ and $D > d$. The new feature vectors $y_i \in R^d$ are defined by the following linear transformation:

$$y_i = V^T x_i, \quad i = 1, \dots, N \tag{1}$$

where $V \in R^{D\times d}$ is a transformation matrix.

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