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A modified stochastic neighbor embedding for multi-feature dimension reduction of remote sensing images

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ABSTRACT

In automated remote sensing based image analysis, it is important to consider the multiple features of a certain pixel, such as the spectral signature, morphological property, and shape feature, in both the spatial and spectral domains, to improve the classification accuracy. Therefore, it is essential to consider the complementary properties of the different features and combine them in order to obtain an accurate classification rate. In this paper, we introduce a modified stochastic neighbor embedding (MSNE) algorithm for multiple features dimension reduction (DR) under a probability preserving projection framework. For each feature, a probability distribution is constructed based on *t*-distributed stochastic neighbor embedding (*t*-SNE), and we then alternately solve *t*-SNE and learn the optimal combination coefficients for different features in the proposed multiple features DR optimization. Compared with conventional remote sensing image DR strategies, the suggested algorithm utilizes both the spatial and spectral features of a pixel to achieve a physically meaningful low-dimensional feature representation for the subsequent classification, by automatically learning a combination coefficient for each feature. The classification results using hyperspectral remote sensing images (HSI) show that MSNE can effectively improve RS image classification performance.

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1. Introduction

In recent years, the advances in earth observation technology, especially in hyperspectral (Landgrebe, 2002) and high-resolution (Acqua et al., 2004) remote sensing, have led to a growing availability of remotely sensed images. These earth observation data provide the opportunity to develop many important applications, which are closely related to the accurate classification of images (Zhu and Blumberg, 2002; Stavrakoudis et al., 2011; Walter and Luo, 2011), e.g., land-cover monitoring, urban planning and growth regulation, environmental damage assessment, military reconnaissance, and so on (Campbell, 2000; Chang, 2003). Image classification is an important issue in remote sensing and other applications. In the remote sensing literature, there are two main groups of approaches for image classification: supervised image classification (Liu et al., 2011; Shao and Lunetta, 2012) and unsupervised image classification (Baraldi and Parmiggiani, 1995). Generally speaking, supervised classification often achieves a higher classification accuracy than unsupervised classification, due o the consideration of discriminative information from the given training samples (Zhong and Zhang, 2012). However, in this case, it is common to perform feature extraction and dimension reduction (DR) (Conese and Maselli, 1993; Harsanyi and Chang, 1994; Zhao and Maclea, 2000; Phillips et al., 2009) before classification, which helps to: (1) remove the redundancy among features, (2) decrease the computational cost, and (3) avoid the Hughes phenomenon (Hughes, 1968).

For the input high-dimensional feature in the original feature space, e.g., the l-dimensional feature vector in the spectral domain (l is the number of spectral channels of the remote sensing image), the DR algorithm aims to find a feature mapping from the original feature space to a lower-dimensional subspace in which some specific desired information can be preserved as much as is possible. For example, the best-known DR algorithm, principal component analysis (PCA) (Jolliffe, 2002), finds a subspace of principal components in accordance with the maximum variance of the input feature matrix. Another popular DR technology, linear discriminant analysis (LDA) (McLachlan, 1992), finds the low-dimensional subspace where the different classes of samples remain well separated after projection. Considering that PCA and LDA are global linear algorithms, which do not work well in nonlinear distributed data conditions (Zhang et al., 2009), some researchers have also proposed nonlinear DR algorithms for remote sensing data. Such

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algorithms include local linear embedding (LLE) (Bachmann et al., 2005), isometric mapping (ISOMAP) (Bachmann et al., 2005), supervised local tangent space alignment (SLTSA) (Ma et al., 2010), local Fisher's discriminant analysis (LFDA) (Li et al., 2012), and spherical stochastic neighbor embedding (SSNE) (Lunga and Ersoy, 2013).

It should be emphasized that, in the aforementioned works, the adopted DR algorithms only deal with a single kind of feature as input, i.e., the spectral feature, which is recognized as the most discriminative feature in remote sensing image classification. Therefore, such an image classification approach processes each pixel independently using its own spectral feature, without considering the spatial relationship of the neighboring pixels. In fact, in remote sensing image classification, it is important to employ multiple features from both the spatial and spectral domains to effectively represent a pixel's information (Segl et al., 2003; Yang and Wang, 2012; Zhang et al., 2012, 2013). Such features include the spectral signature (Vaiphasa, 2006), the morphological property (Benediktsson et al., 2005), the shape feature (Jiao et al., 2012), and so on. Previous studies have reported that combining the multiple features of a certain pixel can improve land-cover classification accuracy (Landgrebe, 1980; Puissant et al., 2005). Since each feature can be viewed as a vector in a high-dimensional feature space, it is essential to consider the complementary properties of different features and combine them in order to obtain an accurate classification rate. A conventional approach is vector stacking (VS) (Huang et al., 2011), which simply concatenates different feature vectors into a long vector, then applies one of the aforementioned DR techniques before the subsequent classification. However, theoretically speaking, these DR technologies can only deal with a single kind of feature as input. In contrast, the direct VS strategy of multiple features intrinsically assumes that the different features are distributed in a unified feature space, although they are not, because they have different physical meanings and statistical properties (e.g., mean and variance). Therefore, it is unreasonable to use simple VS and DR to combine different features for the subsequent classification (Xia et al., 2010).

To overcome this problem, in this paper, we introduce a multiple features dimension reduction algorithm under a probability preserving projection framework, i.e., t-distributed stochastic neighbor embedding (t-SNE) (Maaten and Hinton, 2008). For each feature, a probability distribution is constructed based on t-SNE, and we then alternately solve t-SNE and learn the combination coefficients, i.e., the weighting factors for different features in the optimization. In summary, this modified stochastic neighbor embedding (MSNE): (1) considers multiple features of a pixel to achieve a physically meaningful low-dimensional feature representation for the subsequent classification; and (2) automatically optimizes the combination weighting factors for different features according to their contributions to the subsequent classification, which indicates the complementary properties of different features.

The remainder of this paper is organized as follows. In Section 2, we introduce the proposed multiple features dimension reduction strategy in detail. The experimental results are reported in Section 3, including the description of the study area and dataset, the spatial and spectral feature extraction of the remote sensing image, and the image classification results and analysis. Finally, Section 4 concludes the paper.

2. Modified stochastic neighbor embedding algorithm

The principle of the proposed multiple features dimension reduction strategy is shown in Fig. 1. The MSNE algorithm finds a low-dimensional representation $y \in \mathrm{R}^d$ of input multiple features $\{f^{(k)} \in \mathrm{R}^{L_k}\}_{k=1}^{m}$, in which m is the number of features and k is a specific feature within a population of m features ($k = 1, \ldots, m$), and L_k is the length of the kth feature vector. In order to deal with the out-of-sample problem (Bengio et al., 2004) (see Section 2.3 for a detailed discussion of this issue), only a subset of samples in the image are used as the input data of MSNE. Suppose we are given a multiple features dataset of n samples, e.g., $F = \{F^{(k)} \in \mathrm{R}^{L_k \times n}\}_{k=1}^{m}$, wherein $F^{(k)}$ is the kth feature matrix. In MSNE, we first build a probability distribution $P^{(k)}$ for each feature based on t-SNE. We then alternately solve t-SNE and learn the optimal combination coefficient vector ω to obtain the solution of MSNE. Finally, the linear transformation for MSNE feature mapping is solved by linear regression, and the optimized feature representation in reduced feature space is achieved by such a linear transformation for each pixel of the remote sensing image, respectively.

2.1. t-distributed stochastic neighbor embedding

t-SNE is extended from standard SNE (Hinton and Roweis, 2003), which is designed for single feature nonlinear dimension reduction. Suppose that we have input high-dimensional data samples $X = \{x_1, \cdots, x_n\} \in \mathrm{R}^{L \times n}$, in which n is the number of samples and L is the length of feature vector, respectively. SNE defines the normalized pairwise distances as a joint probability distribution over the input sample pairs, which are represented in a matrix P^s:

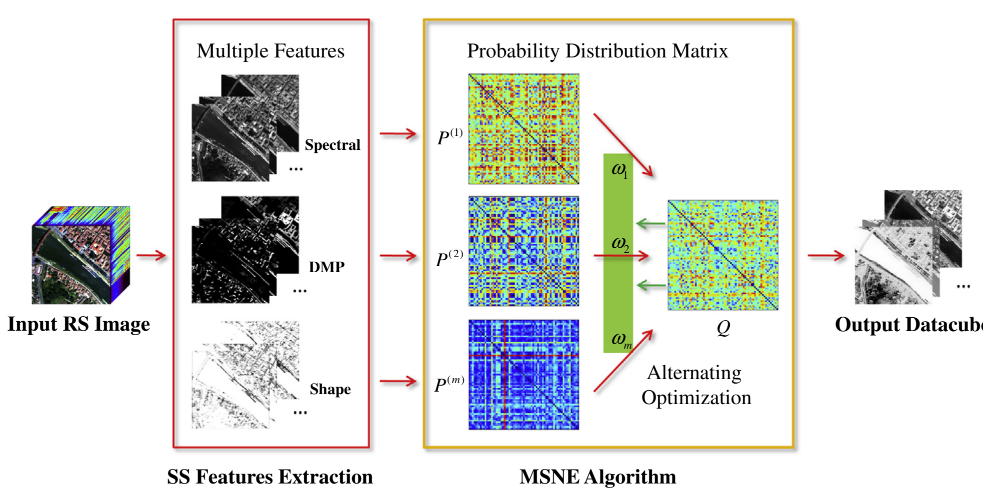

Fig. 1. Flowchart of the proposed multiple features dimension reduction strategy.

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