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Spectral-spatial classification of hyperspectral imagery with cooperative game

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ABSTRACT

Spectral-spatial classification is known to be an effective way to improve classification performance by integrating spectral information and spatial cues for hyperspectral imagery. In this paper, a game-theoretic spectral-spatial classification algorithm (GTA) using a conditional random field (CRF) model is presented, in which CRF is used to model the image considering the spatial contextual information, and a cooperative game is designed to obtain the labels. The algorithm establishes a one-to-one correspondence between image classification and game theory. The pixels of the image are considered as the players, and the labels are considered as the strategies in a game. Similar to the idea of soft classification, the uncertainty is considered to build the expected energy model in the first step. The local expected energy can be quickly calculated, based on a mixed strategy for the pixels, to establish the foundation for a cooperative game. Coalitions can then be formed by the designed merge rule based on the local expected energy, so that a majority game can be performed to make a coalition decision to obtain the label of each pixel. The experimental results on three hyperspectral data sets demonstrate the effectiveness of the proposed classification algorithm.

1. Introduction

Hyperspectral sensors can record hundreds of narrow spectral bands from the visible to infrared spectrum, close to the actual spectrum of the material. Therefore, hyperspectral images with hundreds of continuous narrow spectral bands are an important data source for discriminating different objects based on their spectral differences (Chang, 2003). Hyperspectral image classification can be considered as a labeling problem of mapping the predefined semantic labels to each pixel or clique for a hyperspectral image (Camps-Valls et al., 2014). This is a basic task of many applications, such as urban planning, precision agriculture, and environmental monitoring. As a result, hyperspectral image classification has been the subject of a great deal of attention in the last decade. However, the detailed spectrum results in high dimensionality and redundancy of spectral bands, which brings difficult processing problems, such as the high-dimensionality problem, i.e., the Hughes phenomenon (Hughes, 1968), to hyperspectral image classification. Therefore, the detailed spectral features of hyperspectral images do not always help to improve the performance of classification in the case of limited training samples.

To alleviate the impact of the Hughes phenomenon, a number of dimensionality reduction techniques (Plaza et al., 2005; Kianisarkaleh and Ghassemian, 2016) can be used as a preprocessing step to reduce the dimensionality of the data. In addition, some classification algorithms have the ability to deal with the problem of high dimensionality and limited training sets; for example, support vector machine (SVM) (Melgani and Bruzzone, 2004; Mountrakis et al., 2011) and multinomial logistic regression (Böhning, 1992; Krishnapuram et al., 2005). In recent years, sparse representation (Chen et al., 2011; Xue et al., 2015), which involves sparsely representing the test pixel by a few atoms of a training dictionary, and ensemble learning methods (such as random forest (Belgiu and Drăguţ, 2016) and rotation forest (Xia et al., 2014)), which involve combining multiple classifiers to obtain a better classification performance, have also been successfully used in hyperspectral image classification. These classification approaches process each pixel independently to assign a label based on its

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spectral information, which always results in a salt-and-pepper classification appearance in hyperspectral image classification. Hyperspectral images with a high spatial resolution have become available in recent years, and can provide rich details and texture information about semantic objects, alongside detailed spectral information (Fauvel et al., 2013; Zhong et al., 2016; Wang et al., 2017), to help in the accurate recognition of land-cover classes. However, the salt-and-pepper classification phenomenon is a big problem for hyperspectral images with a high spatial resolution.

In order to improve the performance of classification, the spatial correlation of the images can be fully used, and there have been a number of studies that have focused on the spectral-spatial classification (Fauvel et al., 2013; Han et al., 2017). A typical way to consider the spatial information is an object-oriented classification method. The object-oriented classification (Blaschke, 2010) methods take objects as the basic processing unit, so that they intrinsically provide the spatial information to alleviate the salt-and-pepper classification noise. The objects correspond to homogeneous regions, which can be obtained by segmentation algorithms such as the mean shift segmentation (MSS) approach (Comaniciu and Meer, 2002) and the fractal net evolution approach (FNEA) (Baatz and Schäpe, 2000). Taking objects as the basic unit, direct classification using the object features can be used to obtain the class labels. The other way to obtain the classification result is to use a majority voting strategy (Tarabalka et al., 2010a) within each object based on pixelwise classification. Therefore, object-oriented classification can be considered to combine the classification and segmentation algorithms to achieve the goal of spectral-spatial classification. However, as the key step in object-oriented classification, the segmentation faces the challenge of the selection of the optimal segmentation scale, as a result of the scale diversity of the various land-cover types (Johnson and Xie, 2011).

Another useful classification approach considering spatial information is the random field approach. As an image labeling problem, the image classification task can be successfully modeled as a random field model to capture some of the internal prior information of the image, such as the smoothness and local interactions between pixels. As a widely used random field model, the Markov random field (MRF) model was first introduced into image analysis in 1984 (Geman and Geman, 1984), and has since been successfully applied in various image processing applications (Szeliski et al., 2008; Chen et al., 2012). For hyperspectral image classification, the MRF model can be used to consider the spatial information (Tarabalka et al., 2010b; Jia et al., 2015; Sun et al., 2015). In order to model the interaction between pixels in a flexible way, both in the labels and observed data, the conditional random field (CRF) model, as an improved MRF model, was first applied in image processing by Kumar and Hebert (2003) as a discriminative random field model, after first being proposed to address the labeling of 1-D text sequences by Lafferty et al. (2001) in 2001. In the following years, the CRF model has successfully applied in remote sensing image classification (Zhong and Wang, 2010, 2011; Li et al., 2011, 2013; Zhang and Jia, 2012; Zhong et al., 2014a,b; Zhao et al., 2015, 2016).

In the last two decades, the CRF framework has become very popular in many applications, partly due to the appearance of new, powerful optimization algorithms. The CRF inference problem of finding the image labeling for an image classification application with multiple labels is NP-hard (Li, 2009), so that approximate optimization algorithms have to be applied. The early inference methods, such as iterated conditional modes (ICM) (Besag, 1986) and simulated annealing (Barnard, 1989), often performed poorly with regard to the efficiency or effectiveness aspect for some applications. For example, as one of the most well-known early methods for the optimization of random field energy, the ICM algorithm can be considered as a coordinate descent method that iteratively optimizes the energy with respect to a node by fixing the labels of the remaining nodes. Therefore, it is a greedy strategy to find a local minimum, and has been proved to be ineffective (Szeliski et al., 2008). Compared to the early techniques such as ICM, powerful new inference algorithms, such as graph cuts (Boykov et al., 2001) and loopy belief propagation (LBP) (Yedidia et al., 2000), have since been proposed, which can generally obtain more accurate results with an acceptable efficiency. Taking LBP as an example, it is a popular message passing algorithm for the inference of random fields. The algorithm iteratively uses local message passing for a loopy graph based on the designed message passing scheme to pass messages from the neighboring pixels. Although the algorithm cannot guarantee to converge to a fixed point, due to sticking in an infinite loop between two labels, it has a strong local minimum property and has been proved to be highly effective in various applications (Szeliski et al., 2008; Zhang and Jia, 2012; Zhong and Wang, 2010; Zhong et al., 2014a).

In this work, a game-theoretic spectral-spatial classification algorithm (GTA) based on a CRF model for hyperspectral images is presented. Game theory, which was formally introduced by Neumann and Morgenstern (1944) in 1944, can provide a powerful theoretic framework for optimization problems involving multiple decision-making, and has been successfully applied in a large number of fields, such as economics, evolutionary biology, medical science, and computer science. For image processing, game theory also has many applications. For example, the image semantic labeling problem can be addressed based on the concepts of game theory through a non-cooperative game or a cooperative game (Yu and Berthod, 1995; Berthod et al., 1996; Guo et al., 1998; Ibragimov et al., 2012). There were also a few studies in the 1990s of inference methods based on game theory for the optimization of the energy of random fields. A game strategy approach was proposed by Yu and Berthod (1995) in 1995, in which an n-person non-cooperative game was designed to yield an optimization algorithm that converges to a local minimum. This algorithm is similar to ICM in that each player independently selects its own strategy to minimize its own loss in the non-cooperative game. In the following years, cooperative game theory was used to obtain the labels of pixels, based on a random field model, by designing an n-person cooperative game (Guo et al., 1998). However, this algorithm needs to iteratively form a coalition of players.

In this paper, game theory is applied to spectral-spatial hyperspectral image classification based on a CRF model. In the GTA algorithm, CRF is used to model the image considering the spatial contextual information, and a cooperative game is designed to obtain the labels. The basic idea is to consider the classification as a game, in which the pixels of the image are regarded as the players, and the labels are regarded as the strategies. The payoff functions are related to the objective function of CRF, and can be optimized to obtain the maximum expected payoff of pixels, considering the mixed strategies. This step can be easily parallelized due to the consideration of the local expected payoff, and can be quickly used to establish the foundation for the following cooperative game, without the requirement for multiple iterations, since the mixed strategy can consider the uncertainty of the set of its pure strategies. The coalition, which is the key problem of a cooperative game, is then formed by the designed merge rule based on the prior knowledge of the spatial patterns of the land-cover types, so that a decisive coalition combined with majority game theory can be performed to select the strategy for each player. The GTA algorithm using a CRF model for hyperspectral image classification can be summarized as follows.

1. The game-theoretic framework for image classification is presented. In the framework, the correspondence between image classification and game theory is established.