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Fusion of hyperspectral and LIDAR data using decision template-based fuzzy multiple classifier system

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ABSTRACT

Regarding to the limitations and benefits of remote sensing sensors, fusion of remote sensing data from multiple sensors such as hyperspectral and LIDAR (light detection and ranging) is effective at land cover classification. Hyperspectral images (HSI) provide a detailed description of the spectral signatures of classes, whereas LIDAR data give height detailed information. However, because of the more complexities and mixed information in LIDAR and HSI, traditional crisp classification methods could not be more efficient. In this situation, fuzzy classifiers could deliver more satisfactory results than crisp classification approaches. Also, referring to the limitation of single classifiers, multiple classifier system (MCS) may exhibit better performance in the field of multi-sensor fusion. This paper presents a fuzzy multiple classifier system for fusions of HSI and LIDAR data based on decision template (DT). After feature extraction and feature selection on each data, all selected features of both data are applied on a cube. Then classifications were performed by fuzzy *k*-nearest neighbour (FKNN) and fuzzy maximum likelihood (FML) on cube of features. Finally, a fuzzy decision fusion method is utilized to fuse the results of fuzzy classifiers. In order to assess fuzzy MCS proposed method, a crisp MCS based on support vector machine (SVM), KNN and maximum likelihood (ML) as crisp classifiers and naive Bayes (NB) as crisp classifier fusion method is applied on selected cube feature. A co-registered HSI and LIDAR data set from Houston of USA was available to examine the effect of proposed MCSs. Fuzzy MCS on HSI and LIDAR data provide interesting conclusions on the effectiveness and potentialities of the joint use of these two data.

1. Introduction and background

During the last decade and the near future the number of sensors and satellites has been growing steadily, and the coverage of the earth in space, time and the electromagnetic spectrum is increasing correspondingly fast. Because of these advances in remote sensing sensors and different abilities of each sensor, sensor fusion become a research hotspot in remote sensing and has been extensively studied and applied to many areas since it usually outperforms a single sensor. Based on the existing different airborne and space borne remote sensing sensors, a wide spectrum of data can be available for the same observed site. For many applications the information provided by individual sensors are incomplete, inconsistent, or imprecise. Fusion of information from different sensors can produce a better understanding of the observed site, which is not possible with single sensor (Simone et al., 2002; Pohl and Van genderen, 1998; Du et al., 2013; Dong et al., 2009; Yun, 2004). LIDAR provides accurate height information for objects on the earth, which makes LIDAR become more and more popular in terrain and land surveying. On the other hand, hyperspectral imaging is a relatively new technique in remote sensing that acquires hundreds of images corresponding to different spectral channels. The rich spectral information of HSI increases the capability to distinguish different physical materials, leading to the potential of a more accurate image classification. As hyperspectral and LIDAR data provide complementary information (spectral reflectance, and vertical structure, respectively), a promising and challenging approach is to fuse these data in the information extraction procedure (Dalponte et al., 2008; Swatantran et al., 2011; Zhang et al., 2013; Liao et al., 2014; Debes et al., 2013).

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In the context of remote sensing data classification, different classification strategies are becoming more and more widespread in different applications (Li et al., 2011; Jia, 2002; Goel et al., 2003). Many successful applications of crisp classifications can be found on remote sensing data especially hyperspectral and LIDAR data. In more details, HSI have been successfully used for classification problems that require very precise description in spectral feature space. An extensive literature is available on the crisp classification of hyperspectral images. Maximum likelihood or Bayesian estimation methods (Jia, 2002), decision trees (Goel et al., 2003), neural networks (Del Frate et al., 2007), genetic algorithms (Vaiphasa, 2003), and kernel-based techniques (Müller et al., 2001; Camps-valls and Bruzzone, 2005) have been widely investigated in this direction. One of the most popular crisp classification methods is SVM defined by Vapnik, a large margin based classifier with a good generalization capacity in the small-size training set problem with high-dimensional input space. Recently, SVMs have been successfully applied in the classification of hyperspectral remote sensing data. Camps-Valls and Bruzzone (2005) demonstrated that SVMs perform equal or better than other classifiers in terms of accuracy on HSI.

At the same time, LIDAR provides high resolution horizontal and vertical spatial point cloud data, and is also being used increasingly in a number of applications such as classification, feature extraction and change detection (Brenan and Webster, 2006; Chen, 2010). LIDAR has the advantage of being able to create elevation surfaces that are in 3D. Because of these abilities, crisp classification of LIDAR data into objects such as building, tree and road in complex area is a challenging research topic in pattern recognition and remote sensing studies (Bartels and Wei, 2006; Lodha et al., 2006). Some of these classification researches try to benefit from 3D information of LIDAR data to differentiate between ground and aboveground objects. Axelsson (1999) and Ma (2004) classify LIDAR data into features such as buildings. They try to separate ground and non-ground points from LIDAR data to extract building objects. Some of researches try to extract trees or forests based on the definition of special features on LIDAR data (Li et al., 2013; Ørka et al., 2009).

However in remote sensing, each pixel from different satellites might represent several kilometres of land. A crisp classifier would assign only one class to each pixel, which does not feel natural. In this sense, fuzzy classification would represent more naturally mixtures and transition zone. Also, in the presence of mixed coverage pixels, crisp classifiers produced errors, omission and commission. Theoretically a fuzzy classifier is not affected by such errors and in principle can produce a classification that is more accurate than any crisp classifier. Pepe et al. (2010) compared the performance of crisp and fuzzy classification on remotely sensed data. The results showed that fuzzy classifiers outperformed the crisp classifiers. Related to the field of fuzzy classification of hyperspectral and LIDAR remote sensing data, a number of approaches have been considered (Yamany et al., 1999; Kasiri Bidhendi et al., 2007; Zhang and Qiu, 2012). Yamany et al. (1999) presented a fuzzy system based hyperspectral classifier for automatic target identification. The system is based on partitioning the spectral band space into clusters using a modified fuzzy C-means (FCM) clustering algorithm. Classification of each pixel is then carried out by calculating its fuzzy membership in each cluster. The results showed that the fuzzy hyperspectral classifier is successful in target identification using materials spectrum. Kasiri Bidhendi (2007) applied fuzzy unsupervised classification approaches on hyperspectral data. They used fuzzy C-means clustering and fuzzy relational clustering (FRC). Zhang and Qiu (2012) successfully applied an unsupervised neuro-fuzzy system for classification of hyperspectral data. They used Gaussian fuzzy self-organizing map (GFSOM). Also in fuzzy classification of LIDAR data, Cao et al. (2011) applied an unsupervised approach based on an improved fuzzy Markov random field (FMRF) model for fusion of LIDAR and optical images. In the proposed FMRF model-based approach, the spatial contextual information is applied by modelling the image as a Markov random field (MRF), with which the fuzzy logic is introduced simultaneously to reduce the errors caused by the hard classification. Brzank and Heipke (2006) applied a fuzzy logic concept for classification of LIDAR data into water and land points in coastal areas. They used fuzzy logic to determine a membership value for every point belonging to the class water.

Recently, new researches focus on fusion of HSI and LIDAR data to overcome the weaknesses of each data. Shimoni et al. (2011) used a score level fusion approach for detecting stationary vehicles under shadows, where detection scores from both HSI and LIDAR data are derived separately and combined with a simple sum rule. Zhang et al. (2013) try to fuse HSI and LIDAR data through a physical model for detecting objects under shadow. They developed a simple but efficient illumination correction method to remove the direct illumination component of the observed hyperspectral radiance data, and detected objects under shadows. Liao et al. (2014) proposed a graph-based fusion method to fuse HSI and LIDAR data. Their method first applies feature extraction on each individual data source, then concatenate all the features together into one stacked vector for classification. Finally a graph-based fusion method to couple dimensionality reduction and data fusion of the spectral information (of original HSI) and the features extracted by morphological features computed on both HS and LIDAR data together. Compared to the methods using only single feature and stacking all the features together, their proposed method has more than 10% and 5% improvements in overall classification accuracy, respectively. Debes et al. (2013) introduced a novel framework for combining the HSI and LIDAR data, which enables handling identified objects as uniform entities rather than as independent pixels. Further contributions include an initial spectral unmixing step that segregates noise and significantly improves the benefit of adding LIDAR, as well as the application of ensemble learning in the form of random forest algorithms that inherently support feature selection.

Some of the new researches on fusion of HSI and LIDAR data focused on multiple classifier systems. In such systems a set of classifiers is first produced and then combined by a specific fusion method. The resulting classifier is generally more accurate than any of the individual classifiers that make up the ensemble. Ceamanos et al. (2010) applied a multiple classifier system based on SVM for improvement of classification results on HSI. In the literature of HSI and LIDAR fusion, Zhao et al. (2013) applied four features: MNF (minimum noise fraction), PCA (principal component analysis), NDVI (normalized difference vegetation index) and GLCM (gray level co-occurrence matrix) on HSI. Then three classifiers, maximum likelihood classifier (MLC), SVM and multinomial log regression (MLR) were applied on features of hyperspectral data. On LIDAR data, they separated ground points and non-ground points by Axelsson filter and applied three mentioned classifiers on LIDAR data. Finally, they fused all classifiers with a simple majority voting. Uhlmann et al. (2013) extracted some features from hyperspectral data. Then they combined each of the single features with the original hyperspectral bands and LIDAR data into 5 additional feature sets. In classification step they used SVM with polynomial kernel to classify each feature sets. Finally they applied majority voting to fuse classification maps of classifiers. All the aforementioned papers indicate a good complementary relationship between hyperspectral and LIDAR data, as they contain very different information.

In previous works, classification of HSI and LIDAR data were performed using crisp classification strategies. In his paper we try to propose a fuzzy multiple classifiers system based on decision template for fusion of HSI and LIDAR data. Also, to address the abilities of the proposed method against multiple crisp classifier system for