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Fusion of high spatial resolution WorldView-2 imagery and LiDAR pseudo-waveform for object-based image analysis

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ABSTRACT

High spatial resolution (HSR) imagery and high density LiDAR data provide complementary horizontal and vertical information. Therefore, many studies have focused on fusing the two for mapping geographic features. It has been demonstrated that the synergetic use of LiDAR and HSR imagery greatly improves classification accuracy. This is especially true with waveform LiDAR data since they provide more detailed vertical profiles of geographic objects than discrete-return LiDAR data. Fusion of discrete-return LiDAR and HSR imagery mostly takes place at the object level due to the superiority of object-based image analysis (OBIA) for classifying HSR imagery.

However, the fusion of the waveform LiDAR and HSR imagery at the object level has not been adequately studied. To fuse LiDAR waveform and image objects, the waveform for the objects derived from image segmentation are needed. However, the footprints of existing waveform are usually of fixed size and fixed shape, while those of building are of different size and shape. In order to obtain waveforms with footprints that match those of image objects, we proposed synthesizing object-based pseudo-waveforms using discrete-returns LiDAR data by utilizing count or intensity based histogram over the footprints of the objects. The pseudo-waveforms were then fused with the object-level spectral histograms from HSR WorldView-2 imagery to classify the image objects using a Kullback–Leibler divergence-based curve matching approach.

The fused dataset achieved an overall classification accuracy of 97.58%, a kappa coefficient of 0.97, and producer's accuracies and user's accuracies all larger than 90%. The use of the fused dataset improved the overall accuracy by 7.61% over the use of HSR imagery alone, and McNemar's test indicated that such improvement was statistically significant ($p < 0.001$). This study demonstrates the great potential of pseudo-waveform in improving object-based image analysis. This is especially true since currently the majority of commercial LiDAR data are of discrete return while waveform data are still not widely available.

1. Introduction and background

Fine-scale land cover mapping is essential for a variety of applications, especially in urbanized areas. Urban resource management, maintenance and planning, and pattern analysis all benefit from an accurate and detailed land cover classification. To achieve this, two emerging remote sensing techniques, high spatial resolution (HSR) multispectral imagery and high density Light Detection and Ranging (LiDAR), have been more and more frequently used to develop fine-scale urban land cover maps (Zhou, 2013).

The recent launch of many commercial HSR sensor systems (such as GeoEye-1, Pléiades-2, and WorldView-3) greatly improved the spatial resolution of imagery remotely sensed, with several 1–4 m multispectral bands and a sub-meter panchromatic band. In consort with the increasing availability of HSR remote sensors, object-based image analysis (OBIA) techniques have rapidly developed for fine-scale land cover mapping in the last decade (Blaschke, 2010; Berger et al., 2013; Zhou, 2013). OBIA performs image classification using image objects or segments rather than pixels as processing units. Image objects are generated through an image segmentation procedure with each segment composed of spatially adjacent pixels grouped according to some pre-defined homogeneity criteria (Blaschke, 2010). Many studies have demonstrated that OBIA approaches are superior to the pixel-based image

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analysis for HSR imagery (Ke et al., 2010; Arroyo et al., 2010; Sridharan and Qiu, 2013; Zhou, 2013).

Traditionally, OBIA techniques are based on object-level statistical summaries, such as the mean and standard deviation of all the pixel values of an image object. However, these object-level statistical summaries are representative of the object's characteristics only when the pixel values follow a normal distribution (Pedley and Curran, 1991; Shackelford and Davis, 2003; Berger et al., 2013). Unfortunately, a non-normal frequency distribution is common for spectral pixels values due to the within-object heterogeneity of the HSR imagery (Stow et al., 2012; Sridharan and Qiu, 2013; Toure et al., 2013). Consequently, these statistical summaries may misrepresent the spectral or structural nature of the objects and mislead the subsequent analysis (Sridharan and Qiu, 2013).

To overcome this problem, novel approaches based on object-level spectral frequency distribution (histogram) or cumulative frequency distribution have been proposed for object-based image classification recently (Stow et al., 2012; Sridharan and Qiu, 2013; Toure et al., 2013). By using curve matching approaches they have achieved better performances than using the traditional statistical summaries. Compared to statistical summaries, the curve of an object-level frequency distribution provides a more comprehensive description of the spectral components of an image object, which is sufficient to separate geographic features with distinct spectral characteristics. However, the utilization of this spectral information alone in differentiating between spectrally similar but structurally different features, such as buildings and roads or trees and grasses, is still challenging due to the limited spectral resolution of most HSR multispectral sensors.

Unlike HSR imagery that provides two-dimensional (2D) horizontal spectral information only, the increasingly available LiDAR data offers the third-dimensional (3D) elevation information for geographic features (Koetz et al., 2007). There are two types of LiDAR data based on how the signal is recorded: discrete-return LiDAR and full-waveform LiDAR (Ussyshkin and Theriault, 2011). Discrete-return LiDAR typically records 1 to 6 returns for each transmitted laser pulse. The measurements provided by discrete-return LiDAR, such as elevation, intensity, and the elevation derived digital terrain model, have been intensively used for tree species classification (Zhang and Qiu, 2012), land cover classification (Sasaki et al., 2012), and 3D building roof construction (Kim and Shan, 2011).

Full waveform, a relatively new product of LiDAR, becomes popular in the last decade. It records the quasi-continuous time-varying strength of the return signal from the illuminated area (i.e. waveform footprint) using small time intervals (e.g., 1nanosecond), consequently resulting in thousands of measurements for each transmitted laser pulse (Alexander et al., 2010; Ussyshkin and Theriault, 2011). Due to this finer vertical resolution, the waveform offers an enhanced capability to reflect the vertical structures of geographical objects compared with the traditional discrete-return LiDAR (Zhang et al., 2011; Farid et al., 2008).

To take advantage of waveform LiDAR for land cover classification, some studies have attempted to extract more returns from full waveforms through discretization. The number of resultant returns can be set to be much more than that of the traditional discrete-return LiDAR, and therefore to better represent the vertical structure of objects (Wagner et al., 2006; Reitberger et al., 2009; Mallet and Bretar, 2009; Yao et al., 2012). The discretized returns then can be analyzed by the existing algorithms designed for traditional discrete-return LiDAR. Other studies were based on analyzing the waveform-derived metrics, such as the number of echoes, peak amplitude, echo width, and ground peak location, which are extracted to represent the important characteristics of the waveform shapes (Zaletnyik et al., 2010; Mallet et al., 2011; Wang et al., 2012; Zhuang and Mountrakis, 2014; Guo et al., 2011). The results of these researches demonstrated positive correlations between those waveform-derived metrics and the corresponding backscattered surface material within the footprints. Nevertheless, waveform LiDAR alone may not sufficiently separate structurally similar but spectrally different target features (e.g., road and grass) (Geerling et al., 2007), although it provides much more vertical structural information than discrete-return LiDAR.

Overall, HSR multispectral imagery and waveform LiDAR data have their distinct advantages and disadvantages for fine-scale land cover mapping. HSR multispectral imagery provides accurate spatial information and moderate spectral information but lacks vertical structural information. On the other hand, waveform LiDAR data provide accurate vertical structural information but limited horizontal spectral information. Fusion of these two data sources is an obvious approach in order to capitalize on their respective advantages and compensate for their respective shortcomings for fine-scale land cover classification (Lee et al., 2008; Anderson et al., 2008).

According to Zaletnyik et al. (2010), waveform LiDAR data can also be conceptually considered as a time-varying frequency distribution of returning impulses. This leads to the idea that the 3D waveform LiDAR data, like the 2D spectral information from the HSR imagery, can also be analyzed as a frequency distribution. The curve of the vertical distribution of waveform contains substantially more information than waveform-derived metrics and the discretized returns. Therefore, the synergetic use of frequency distributions for both the object-level spectral data and for the waveform LiDAR data through data fusion is therefore expected to deliver better classification results by taking full advantage of both the horizontal spectral and vertical structure information. This idea, to the best of our knowledge, has not yet been investigated in the literature.

To integrate the waveform LiDAR data into an object-based image analysis, a major challenge needs to be overcome before subsequent data fusion. Currently the footprints of all full-waveform LiDAR are of a fixed size and shape, be it large, medium, or small, while the footprints of geographic objects vary dramatically in size and shape and seldom match those of the waveforms. This obstacle makes it difficult to fuse waveform and spectral frequency distributions of an image object to perform an object based image analysis. The solution we provided in this study is to develop an original method to synthesize object-level pseudo-waveforms with varied footprint sizes and shapes corresponding to that of different objects using discrete-return LiDAR data. As a result, we can easily fuse the synthesized pseudo-waveform curve and spectral histogram curves at the object level for fine-scale land cover mapping.

To assess the object-to-object similarity based on the fused frequency distributions, a discrete Kullback–Leibler (KL) divergence based classifier was proposed. As a non-parametric approach, KL divergence does not require normality of the probability distribution and has been widely used in speech and image pattern recognition (Olszewski, 2012) and in hyperspectral image classification (Ghiyamat et al., 2013). Given that both pseudo-waveform and spectral histogram can be considered as a discrete probability distribution function, the KL divergence based classifier may be useful for classification of the fused frequency distributions.

2. Study area and data

2.1. Study area

The study area is situated in the Turtle Creek Corridor in Dallas County, Texas (Fig. 1), bounded approximately by 96.811° to 96.798°W in longitude and 32.8° to 32.82°N in latitude. It covers