LIDAR-GUIDED ANALYSIS OF AIRBORNE HYPERSONTAL DATA

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ABSTRACT

This paper describes a new framework to the collection and fusion of multisensor airborne LiDAR and hyperspectral data. We describe a data fusion philosophy that provides a spatially precise positioning of hyperspectral data based on discrete first and last return LiDAR data. Three dimensional objects defined by the LiDAR data are then used to sample optimal spectra for subsequent analysis. The sampled spectra retain their positioning metadata and so can be mapped back into geographic space for further analysis. While the paper presents this philosophy within the context of a species classification, other analytical analysis can be performed.

Index Terms— Hyperspectral, LiDAR, data fusion

1. INTRODUCTION

Technologies are now emerging that permit multiple smaller sophisticated sensors to be co-mounted on a single small airborne platform. This allows us to acquire multiple data types over an area with a single acquisition. The advantages of these multisensor configurations are numerous. The first is a reduced cost so that not only does a project need only to budget for a single flight, but with smaller airframes the attendant costs are also reduced. This permits access to the data to a much broader researcher/user community. The second advantage, and one that speaks to the research directly, is the relative ease by which the data can be spatially and temporally fused. This fusion facilitates the development of integrative approaches for data extraction.

One of the more common recent technology fusions has involved the use of active Light Detection and Ranging (LiDAR) and passive optical data, ranging from digital aerial photographs [1] to hyperspectral imaging spectrometers [2]. The advantage of combining these two sensor types is that we can acquire detailed measurements pertaining to both the form and functioning of surface reflectors or objects. The use of very high spatial and spectral resolution imaging spectrometers along with high frequency LiDAR systems allows us to discriminate objects based on their form and measure their biophysical properties and functioning. While there have been numerous projects that have reported on the use of multisensor data, very few describe collection of data from these two technologies simultaneously.

One of the exceptions is the work carried out by Asner [3]. This paper describes portions of a processing framework representing the integration of LiDAR and a full range imaging spectrometer (along with digital photography) onto a single airborne platform. This platform was named MAP-1 (Multisensor Airborne Platform). The LiDAR used is a 150kHz discrete first and last return system. Flying at an altitude of 1500 metres above ground level (AGL) and with a 50kHz pulse rate, results in a LiDAR posting density of ca 1 point / sq metre. Each of these postings has a footprint (the diameter of the light beam that intercepts the surface, analogous to the smallest resolvable unit) of ca. 20cm. The imaging spectrometer system used (Specim’s AISA Dual) is one that covers a range of 400 to 2500 nanometres (nm). There are two spectrometers configured to collect a contiguous data cube within that range. The first covers the Visible/Near Infrared (VNIR) range of 400 to 1000 nm with a bandwidth of 2.3 nanometres Full Width Half Maximum (FWHM), while the second covers the Shortwave Infrared (SWIR) range from 1000 to 2500 nm with bands with a spectral bandwidth of 5.8 nm FWHM. This results in a final hyperspectral data cube with 492 channels. At the flying height of 1500 m AGL the spatial resolution of the data cube is 2 metres. The sensors are mounted in a fixed mount attached to the airframe so an inertial measurement unit (IMU) is required to provide the attitude data during the flight. An Applanix 410 is currently used in this role. The absolute positioning of the aircraft is supplied by a DGPS that is tied to ground controls established at the time of the survey.

2. ORTHORECTIFICATION

Traditional digital orthorectification of airborne imagery has relied on a ray tracing process to determine the location of the terrain relative to the aircraft [4], where the terrain shape is typically defined by a digital elevation model (DEM). In addition, parametric orthorectification uses as inputs aircraft positional parameters from IMU/DGPS systems, so that the resulting process does not require the locating of ground control and tie points [4]. The resulting image is geometrically corrected for aircraft motion and location, and spatially accurate based on the underlying terrain shape. This approach to correcting airborne scanner data is the generally accepted approach [4, 5].

The underlying methodology behind this approach is based on the use of relatively coarse spatial resolution (typically 10 to 20 metres) data where the input of a commonly available DEM will be sufficient for most applications. The elevation models commonly used to orthorectify these data represent an estimation of the ground surface derived from sources such as aerial photography, or active microwave systems such as that delivered by the Shuttle RADAR Topography Mission (SRTM). Recent advances in imaging technologies have given us the opportunity to generate an optical dataset with a large number of spectral channels, and a very high spatial resolution, so that images with 2 metre, or finer, spatial resolution and composed of 300, or more, spectral bands are possible. To take advantage of the fine spatial resolution in, for example, deriving multiple spectra for individual objects, or in maximizing the S/N, a much finer elevation model is required that defines the reflective surface, and not the underlying topography. In other words we require a digital surface model (DSM) that will accurately position the fine resolution pixels relative to any three dimensional object found on the ground. To achieve this level of detail we are increasingly turning to LiDAR to define the DSM. Discrete high frequency LiDAR can, depending on the flight parameters, can yield a point density of 1 or more elevations per square metre.
Our orthorectification used a commercially available software package Caligeo (http://www.specim.fi/) intended to be an inclusive processing tool for the AISA hyperspectral data. The software supports a parametric orthorectification approach that relies on a ray-tracing solution to define the position of the reflective surface relative to the MAP-1 sensor package. To define this surface we generated a DSM based on a strategy to define the top of the reflective surface. This model, termed TORS (top-of-reflective-surface), relies on the extraction of the height representing the maximum height of the LiDAR points within the area representing the hyperspectral pixel, as opposed to an interpolation strategy that employs an averaging of the heights within the pixel. The precision of the placement of the hyperspectral data falls within +/- 1 pixel, see figure 1.

![RGB Images from the hyperspectral data cube with LiDAR intensity](image)

**3. LiDAR-GUIDED SAMPLING**

Our initial goals were to characterize the forest functioning as it related to composition and health with the hyperspectral data. For a geographically large area, acquiring a spatial and spectral resolution yields a data set with particular characteristics. Given a spatial resolution of 2 metres and 492 channels, the resulting image cube can be unwieldy. For example, a 60,000 hectare region of interest yielded an orthorectified database size of 1 terrabyte. The second aspect is related to the quality of the data. We have found that high spatial resolution data in a forested environment are highly influenced by shadowing, with the result being that there is a very high variability in the signal to noise (S/N) within a relatively small area, typically 1 or 2 pixels.

As our interests in addressing issues related to forests are focused on species identification and addressing forest health, we needed to eliminate a large proportion of the pixels that either did not relate to the forest canopy, or that represented an unacceptably low S/N. To achieve these goals we used the LiDAR data to filter “unwanted” pixels. This was achieved in one of two ways - at the plot and individual tree levels. The value of the orthorectification process discussed above therefore becomes apparent as we need to accurately define the hyperspectral pixel within a spatial context relative to the LiDAR data.

**3.1 Plot level**

Plot level analysis was through the use of a top-of-canopy (TOC) LiDAR heights. The top of the dominant-codominant canopy has been defined through the use of the height distributions of LiDAR data. A commonly accepted definition is to use the 75-90th percentile [6] of the vertical point distribution within a user defined cell. The size of the grid cell will be determined by the size of the trees, with larger-crowned trees having designated a larger grid cell size. The hyperspectral data are overlain on the TOC layer and all pixels below the height of the 85th percentile removed from the analysis. The result is that while the entire image is not classified, the top of the canopy is, minimizing confusion from increasingly shadowed pixels lower in the canopy. In this case the data are retained within their image matrix format.

**3.2 Tree level**

An alternative to the use of a plot-level analysis is one that focuses on the definition of individual trees. The advantage of this approach is one where the trees, when defined, can be treated as objects and metadata relating to individuals stored in a separate tree list. The approach used to define the tree tops was based on modifications to techniques developed for passive optical imagery [7-9]. The basic assumption relied on with this initial work, based on passive optical imagery, was that the brightest pixel represented the top of the tree. While the logic of this assumption might be questioned (with respect to orientation of illumination) for this type of imagery, it does hold for LiDAR data where the highest value represents the LiDAR-measured top of the tree. In our analysis we gridded the vegetation point cloud to a 1 metre resolution surface. The gridding algorithm used the highest point found within the one metre grid cell as the representative height when more than one LiDAR postion occurred within a designated grid cell. In most cases however only one point was located within a grid cell. A local maximum filter was fitted to the new surface. This filter is designed to meet a criterion that requires a peak value to be surrounded by lower values. The weakness of this approach is that smaller tree crowns will not be resolved by a 1 metre pixel grid. In this case the smallest crown diameter will be 3X3 metres in size. Independent validation of this approach applied to LiDAR data indicates that an overall accuracy of 85% is achievable when mapping the dominant-codominant tree top locations in dense oldgrowth conifer forests. To accurately map smaller tree crowns a much higher density LiDAR survey is necessary. The advantage of using LiDAR data rather than data from passive optical sensors is that we can control for canopy height and confidently remove those stands, and individual reflective features, that fall below a specified height threshold. In this way we also remove many of the commission errors that were encountered with the passive optical data where the selection criterion was met, but not related to individual trees. The accuracy of this approach has been vetted using both the passive optical [8] as well as the LiDAR data [10]. One caveat on this approach as pointed out by Popescu is that while the accuracies remain high for conifer species, due to their conical shapes, the same cannot be said for many deciduous species. In the case of the latter another approach to tree discrimination must be derived.

Once mapped the location of the individual tree tops are mapped onto the orthorectified hyperspectral data and a spectrum representing the LiDAR-measured top of each tree is extracted.
The advantage to this approach is that from the 1 metre gridded LiDAR data we generate an object representing each individual tree, which is scale/resolution independent (for data with a spatial resolution greater than 1 metre). The resulting locations are therefore easily integrated with the 2 metre hyperspectral data. The resulting tree list stores the location, LiDAR-measured height, and a spectrum for each object. The objects can be mapped back into a geographic space once analysis is complete and scaled up to suit subsequent applications/users.

3.3 Comparison of Spectra

The usefulness of this approach to sample representative spectra was tested using three sampling approaches. The first was to sample from the TOC reflectance spectra as per the plot-level approach. The second approach extracted spectra based on the treetops defined by the LiDAR data. The final sampling strategy employed a manual interpretation of tree tops from the 2 metre imagery. All three samples were derived from the same conifer stands.

Figure 2a represents the signal strength of the spectra sampled from the conifer canopy using the three strategies outlined above. The spectra representing the two LiDAR guided sampling strategies yielded considerably higher reflectance than was the case with those spectra that were sampled using a manual interpreted approach. In addition, the variability of the samples (figure 2b) indicates that the overall variance of the manually sampled spectra are considerably higher than those obtained from the LiDAR-guided approach.

The outcome of this is that with the LiDAR guided sampling we have a much stronger signal with less noise, which should yield a much more consistent result for feature extraction.

4. SPECIES IDENTIFICATION

For the purposes of our work a Spectral Angle Mapper approach [11] was used to classify the data extracted spectra into species. The algorithm was implemented on individual spectra rather than the entire image. To train the classifier, pure stands of each species were identified from field and airphoto sources (the MAP-1 system collects 25 cm. resolution true colour photography simultaneously with the LiDAR and hyperspectral imagery). To address the separability of each of the classes a leave-one-out cross-validation approach was adopted where the SAM classifier was applied iteratively to the data set on n-1 samples. The species class of the sample that was omitted was compared against that predicted by the SAM. The output of this assessment is presented in figure 3.

The overall ability of the classifier to predict the observed species was 76% (kappa = 0.65). When addressing the individual species however the areas of confusion become apparent. There was considerable confusion between Douglas-fir (Pseudotsuga menziesii var. glauca) (termed Fir in figure 3) and white spruce (Picea glauca var. albertana), and to a lesser degree Balsam-fir (Abies lasiocarpa), although this was expected given the physical similarities of the species, and low number of pure stands from which to sample. The pine (P. contorta var. latifolia) distinguished from the other conifer species as did the yellow cedar (Chamaecyparis nootkatensis). Deciduous vegetation, including predominantly poplar (populus spp.) and willow (salix spp.), were grouped and separated from the other spectra.

We also identified beetle infested individuals (pine) at the red-attack stage (highly chlorotic foliage), which had very distinct and unique spectra. The classification accurately predicted the presence of most of the observed species. Spruce was the species that had the lowest success rate, while other species had success.

Figure 3. Confusion matrix of observed vs predicted species spectra based on SAM classifier.
The concurrent collection of airborne LiDAR and hyperspectral data is yielding unprecedented data analysis opportunities. Initial advantages come from rapid and accurate positioning of the hyperspectral data. This positioning is absolute, based on the DGPS, as well as relative based on the INS and DSM. The use of the LiDAR to define objects based on *form* along with the positioned hyperspectral data to yield the samples with the highest S/N to better and more consistently delineate *functioning*. While the data configuration described in this paper yield relatively coarse resolution imagery and sampling, a finer resolution imagery and higher LiDAR posting density will allow us to obtain multiple samples within objects, to characterize spatial characteristics of within object processes and features observed.

5. DISCUSSION
The concurrent collection of airborne LiDAR and hyperspectral data is yielding unprecedented data analysis opportunities. Initial advantages come from rapid and accurate positioning of the hyperspectral data. This positioning is absolute, based on the DGPS, as well as relative based on the INS and DSM. The use of the LiDAR to define objects based on *form* along with the positioned hyperspectral data to yield the samples with the highest S/N to better and more consistently delineate *functioning*. While the data configuration described in this paper yield relatively coarse resolution imagery and sampling, a finer resolution imagery and higher LiDAR posting density will allow us to obtain multiple samples within objects, to characterize spatial characteristics of within object processes and features observed.

6. CONCLUSIONS
The use of LiDAR collected concurrently with hyperspectral data has proven advantages in georeferencing and selection of spectra. The use of LiDAR to define *form* while the hyperspectral data provides information on *function* yields important increases in the dimensionality of analysis and interpretation formerly unavailable from two dimensional data alone.

7. REFERENCES


