CLASSIFYING COMPRESSED LIDAR WAVEFORM DATA

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ABSTRACT

Full waveform recording is becoming increasingly affordable and, consequently, available in today's state-of-the-art LiDAR systems. Therefore, there is no practical limitation to the complexity of pulse detection and other methods that can be applied in post-processing mode. Analyzing the entire return signal, the full waveform can provide additional geometrical and physical information about the reflecting surfaces. Currently, most LiDAR applications are based on utilizing only the geometry of the point cloud, where both the precision and density of these points primarily depend on the peak detection method used in real-time during data acquisition. Analyzing the properties of the full waveform in post-processing, additional information can be obtained that can provide a better geometrical description of the surface (point cloud) and object classification information that can be used, for example, for land cover classification. Since the storage requirements for waveform are quite significant for modern LiDAR systems because of the high-pulse rate, compression is an obvious choice to reduce storage and data transmission requirements. Though the original waveform can be fully reconstructed from the compressed format and used for waveform analysis in post-processing mode, an interesting question is whether the compressed format can be directly exploited for classification and/or peak detection. The objective of this paper is to investigate the feasibility of using the compressed domain waveform data for land cover classification and peak detection.

KEYWORDS: Airborne LiDAR, Data Compression, Classification, Land cover

INTRODUCTION

Airborne LiDAR (ALS) has become the primary source for surface data at the local scale and is widely used in many applications, including digital elevation model generation, city modeling, forest parameters estimation, etc. (Shan and Toth, 2009). The first LiDAR systems were only capable to detect one backscattered echo per emitted pulse (first return). Later the first and last echoes became available, followed by multi-echo or multiple pulse LiDAR systems that are able to measure up to six pulses with intensity characterization of the returns. The newest generation of LiDAR systems, the full-waveform systems, are able to digitize and record the entire backscattered signal of the emitted pulses, the waveform (Mallet and Bretar, 2009).

For a long while, waveform processing has been limited to a few applications, such as earth sciences and forestry mapping, mainly due to cost consideration. As waveform is becoming not only widely available but increasingly affordable, it is expected that waveform processing will be an integral component of topographic mapping in the near future. Waveform processing has the potential to provide users with better information content, including (1) improved peak detection, which could result in better point cloud quality, (2) better macro/micro surface characterization, such as surface orientation, and (3) enhanced surface material signature identification that can be used for object classification.

Waveform processing can be implemented both in real-time (onboard) or post-processing modes. Since there is no need for real-time data processing in most LiDAR applications and the computer power is somewhat limited on data acquisition platforms, waveform processing is mainly developing as a batch processing tool. Despite rapid advancement in storage technologies, waveform still represents a formidable amount of data, which is generally highly redundant due to uniform (equidistant) sampling. In addition, the processing of this large amount of data is also more time consuming due to data transfer and processing requirements. Therefore, waveform compression is an important component of waveform processing as it can serve two purposes: (1) to limit data storage and transfer requirements, and (2) to support feature extraction in the reduced representation domain.

The main goal of this paper is to investigate the feasibility of using the compressed domain for waveform processing. First the waveform compression alternatives are considered, and then land cover classification and peak detection based on the compressed domain representation is studied, including experimental results.

WAVEFORM COMPRESSION

Data compression methods, in general, can be divided into two main groups: lossless and lossy compression. Lossless compression algorithms, like run length encoding (RLE), Huffman coding or arithmetic coding, provide an exact reconstruction of the compressed data, with a somewhat limited compression rate (that depends on the information content of the data). In contrast, lossy compression schemes, like transform coding techniques, provide the user the opportunity to choose between better reconstruction quality and better compression rate. Today's most widely known compression techniques (e.g., JPEG, MP3) are based on lossy compression methods utilizing Fourier or Fourier-related transformation techniques. Recently, methods utilizing the discrete wavelet transform have been developed (e.g., JPEG2000). Compressive Sensing (Baraniuk, 2007) or Compressed Sampling (Candès and Wakin, 2008) is a new promising compression technique that provides good compression rates if certain signal conditions are met.

The performance of most compression techniques depends a lot on data characteristics, as the methods can take advantage of the statistical properties of the data being compressed. Data complexity has the primary impact on the achieved compression rate in general. But knowing frequently occurring patterns in the data can allow for the customization of many compression methods that can result in further improvement in performance. For example, compressing high-resolution airborne imagery is a more generic task compared to LiDAR waveform compression, as the image scene can vary almost limitlessly for the airborne images, while a waveform shows much less diversity in appearance.

To assess the potential of waveform compression, various compression techniques were tested using two LiDAR data sets, including 440 waveforms acquired over Scarborough (Toronto), Canada, by Optech in 2005, and 1022 waveforms, acquired over Beaver Creek (Dayton), Ohio, by Woolpert in 2010. Both areas represent mixed urban and rural environments, including residential buildings, roads and vegetated areas. The Beaver Creek area has more vegetation and therefore shows more variety in waveform. Both publicly/commercially available software and in-house developed compression implementations were used in the testing.

Lossless compression techniques are clearly not practical for LiDAR waveform compression. First, there is no need for 100% correct signal reconstruction, as the waveform signal is noisy. Second, lossless compression is generally very computation intensive and, in addition, provides modest compression rates. Nevertheless, a few lossless methods were tested to have a basic idea of the achievable performance.

There are a large number of lossy compression schemes, including transform-based and pattern-based methods. The usual steps of transform-based lossy compression techniques include:

- Preprocessing of the signal/image to be compressed (e.g., partitioning an image into smaller blocks)
- Transformation, typically using an orthogonal basis (e.g., FFT, discrete cosine transformation, DWT, etc.)
- Quantization of the coefficients; dropping coefficients based on some criterion, such as the order of magnitude or other properties, and then storing the remaining coefficients in a more compact form
- Further lossless compression of the coefficients

From several transform-based compression methods, the discrete wavelet transformation (DWT) appears to be a suitable choice for LiDAR waveform compression, as this transformation exhibits good spatial and frequency domain localization. In an earlier study (Laky *et al.*, 2010a), the CDF (Cohen-Daubechies-Feauveau) wavelet family, with parameters 3 and 9, was chosen for waveform compression studies, as it produced the smallest average reconstruction error around the compression ratio of 20%. Fig. 1 shows a waveform reconstructed at various levels; note that at level 4, corresponding to the detail levels 0 to 4, the waveform is restored to more than 99.9% of the original signal power. Level 4 requires, one-fourth of the wavelet coefficients, so this represents a 25% compression rate.

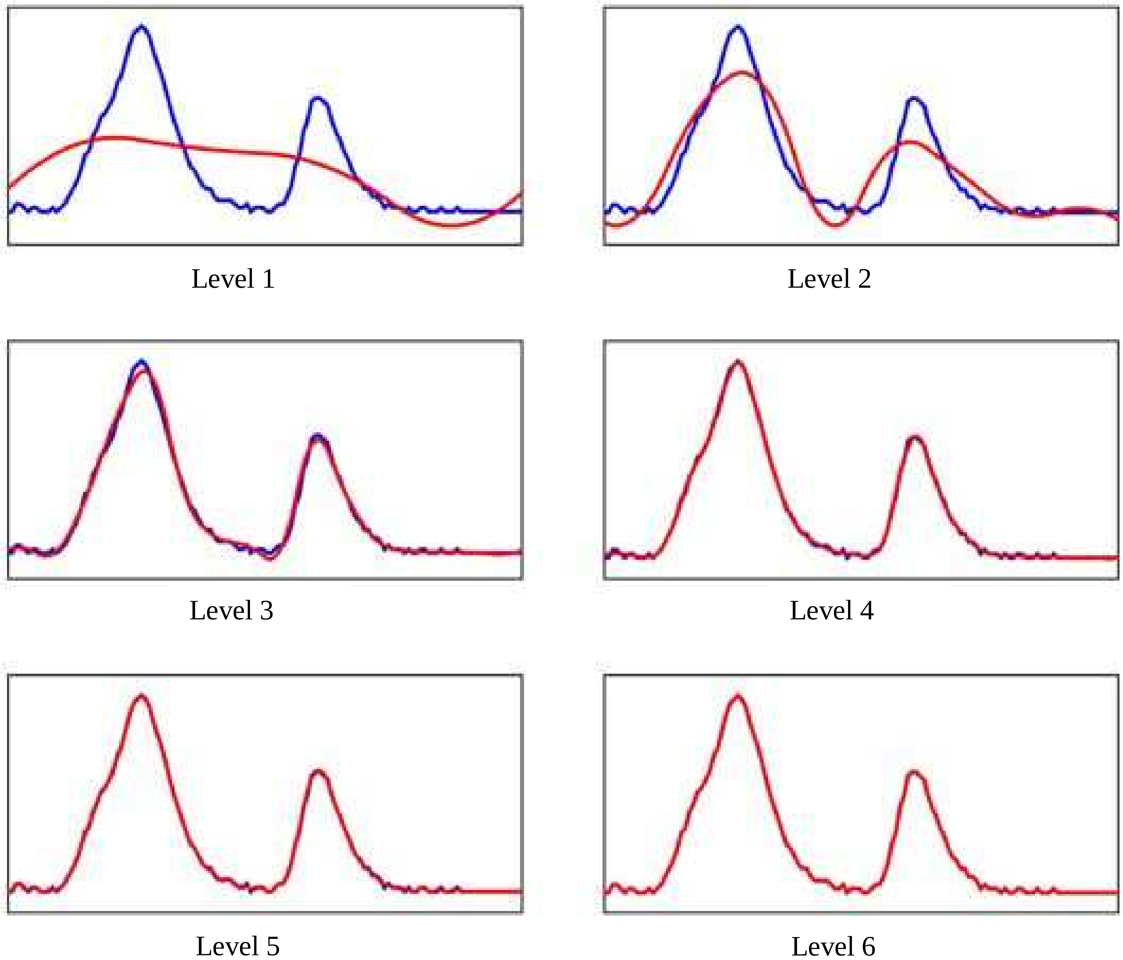

Figure 1. DWT-based waveform reconstruction at various levels (Scarborough data set).

Pattern or shape-based compression methods work in the signal domain and aim to reconstruct the signal from basic shapes. This technique is routinely used to decompose LiDAR waveforms into the sum of shape components, or echoes (pulses/peaks), to generate a denser and more accurate 3D point cloud (Mallet and Bretar, 2009) by modeling the waveforms with Gaussian (Wagner *et al.*, 2006), Generalized Gaussian or lognormal functions (Chauve *et al*., 2007). Fig. 2 shows a Gaussian function-based reconstruction of a rather complex waveform, where seven shapes were required (equivalent to seven peaks detected); the reconstruction error is also shown.

The shape-based decomposition of waveform clearly provides a good performance for compression. In LiDAR mapping terms, for efficient multiple overlapping peak detection, the number of parameters depends on the shape type; for Gaussian function, three parameters are needed, amplitude, mean, and variance. For the case shown in Fig. 2, there are 21 coefficients (3 x 7) instead of the close to 200 samples, representing about a 10% compression rate. The high performance, however, comes at a price, as the method is iterative and requires a significant amount of computations, though good initial approximations can substantially reduce the processing time. If the emitted pulse is recorded and thus available, the shape-based method can take advantage of it, and the problem can be formulated as a de-convolution.

A performance comparison of the various compression methods tested in our study is provided in Table 1. Note that the results shown are based on the 440+1022 waveforms processed that may not be representative. In addition, as LiDAR systems continue to improve, the characteristics of waveforms are also changing, such as better resolution and smaller noise level. Furthermore, the Gaussian-function-based compression works only for waveforms that were generated by a Gaussian pulse. Finally, the computation time varies over a large scale, and it is difficult to characterize it as not all the programs were optimized for fast execution.

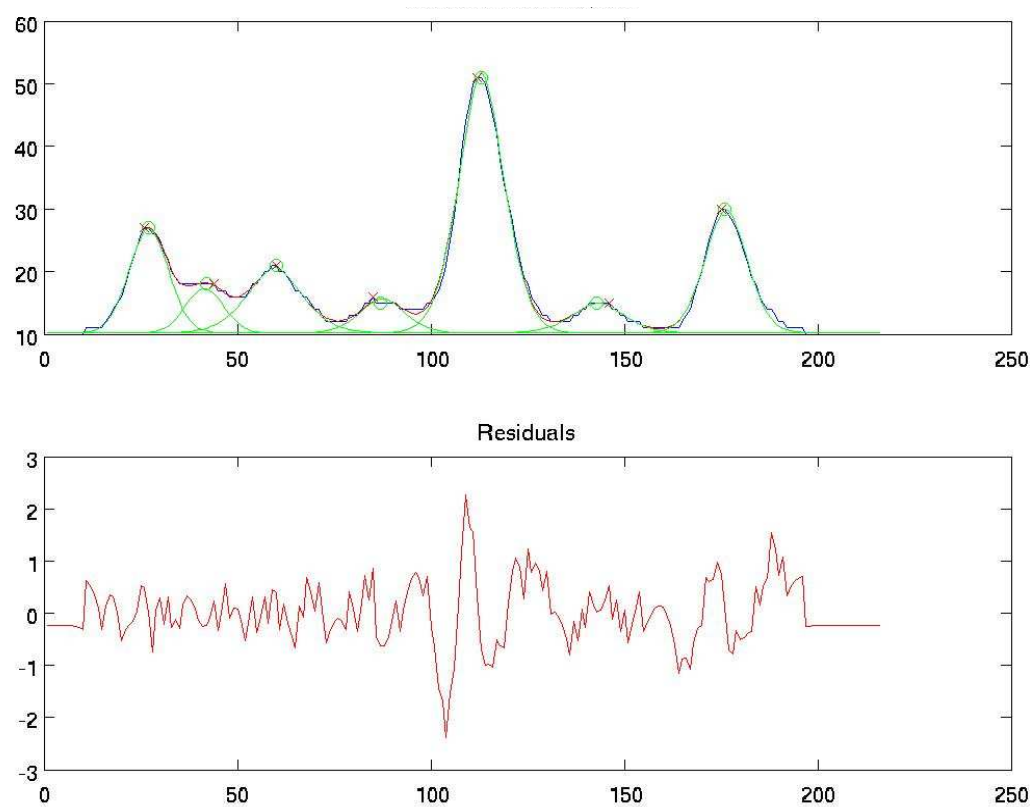

Figure 2. Gaussian function-based waveform reconstruction (Beaver Creek data set).

Table 1. Compression performance of various methods

Compression Type	Compression Method	Compression Rate	
		Maximum [%]	Minimum [%]
Lossless	Info-ZIP	39	47
	GNU GZIP	39	47
	BZIP2	24	26
Lossy	DWT (CFD/3/9)	17	22
	Gaussian function	1	10

FEATURE EXTRACTION

Initially LiDAR was considered a direct data acquisition tool to obtain mass points from the surface of the earth and objects at local scale. Back then the point density on the ground was modest; the point cloud provided a sparse sampling of the object space that was good to describe smooth flat or slowly changing areas, such as rolling terrain, but detecting natural and man-made objects with rapidly changing surface orientations was just not feasible. As LiDAR systems continued to advance, the extraction of various features/objects became a possibility. The introduction of multi-return systems provided an excellent way to identify vegetated areas, which was a powerful capability, not available in airborne image-based photogrammetry. Then, the increased point density allowed for the coarse delineation of surface boundaries, such as surface intersections at roads and buildings. Nowadays, building extraction from the LiDAR point cloud is a common task in LiDAR mapping (Bingcai *et al.*, 2011).

As waveform is becoming widely available for topographic applications, the question is: What benefit can waveform processing offer? More precisely, waveform processing has the potential to provide users with better information content to support improved peak detection, better macro/micro surface characterization, and enhanced surface material signature identification that can be used for object classification, but what can be realized from these promises? In our investigation, we pose the question in a slightly different way. Since LiDAR waveform can be well compressed, and the compressed form provides a near perfect representation of the waveform, the question is whether this compressed domain waveform data can be utilized for feature extraction. From the theory, it is known that the compression is based on the signal power preservation. But signal power may not equal information content. Therefore, experiments were carried out to test object classification and point cloud generation based on waveform data.

Classification Based on DWT Waveforms

The compression domain has some interpretation in terms of wavelet functions, but there is no direct connection to the object space. Therefore, an unsupervised classification test using around 6000 waveforms was performed on a smaller area selected from the Scarborough data set, including four classes: residential buildings, driveways, roads and grassy areas. The advantage of unsupervised classification is that there is no need to have a priori knowledge of the class types belonging to a training or test data set. Kohonen's Self-Organizing Map (SOM), which was first described as an artificial neural network model by Teuvo Kohonen (Kohonen, 1990) was selected for our experiments. The input of the classifier was the 16 coefficients of DWT (CFD/3/9), and there was a simple rule-based additional processing step to refine the SOM classification results; more details are found in (Toth *et al.*, 2010). Fig. 3 provides a visualization of the area and the waveform classification. Table 2 shows the results of the classification, which used 700 randomly picked waveforms that were manually classified. The sum of the percentages in the diagonal is 88.9%, a rather impressive classification result for four classes. The worst case of the misclassification is 6.1% of the points, which have been manually classified as tree, but classified as grass in the SOM approach.

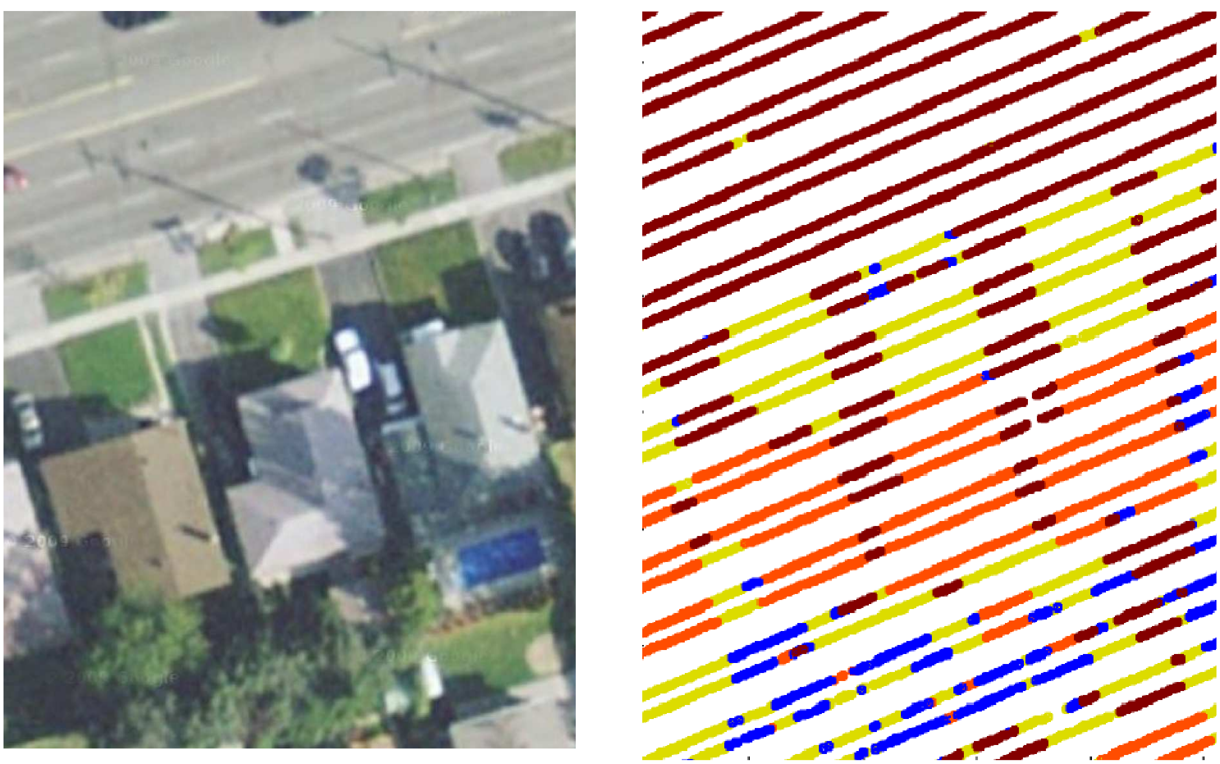

Figure 3. Classification based on DWT waveforms (Scarborough data set).

Table 2. Comparison of the manual and the SOM-based classification; rows: manual classification, columns: SOM-based classification; numbers are the percentages of the manually-classified points in the respective categories

	Grass	Tree	Roof	Pavement
Grass	**20.4%**	0.3%	0.1%	1.9%
Tree	6.1%	**7.0%**	0.4%	0.0%
Roof	0.4%	0.0%	**25.9%**	0.0%
Pavement	0.6%	1.3%	0.0%	**35.6%**

Gaussian-function-based Classification

In other experiments, the shape-based compressed waveform was the input data for classification. The waveforms were processed to obtain the Gaussian-function-based decomposition and then separated into two classes: one-echo or multiple-echo waveforms. The multiple-echo waveforms were classified as trees or roof and the one-echo signals were treated as probability density functions, to determine important statistical parameters, according to their shape, such as the maximum value of intensity (amplitude), standard deviation (pulse width), skewness (measure of the asymmetry of the waveform, third central moment) and the kurtosis (measure of the peakedness, fourth central moment). These parameters are then used as input parameters for the SOM classification. To improve the distinction between road and roof classes, the local range differences were calculated and used in a second step. Additional details on the implementation can be found in (Zaletnyik *et al.*, 2010; Laky *et al.*, 2010b).

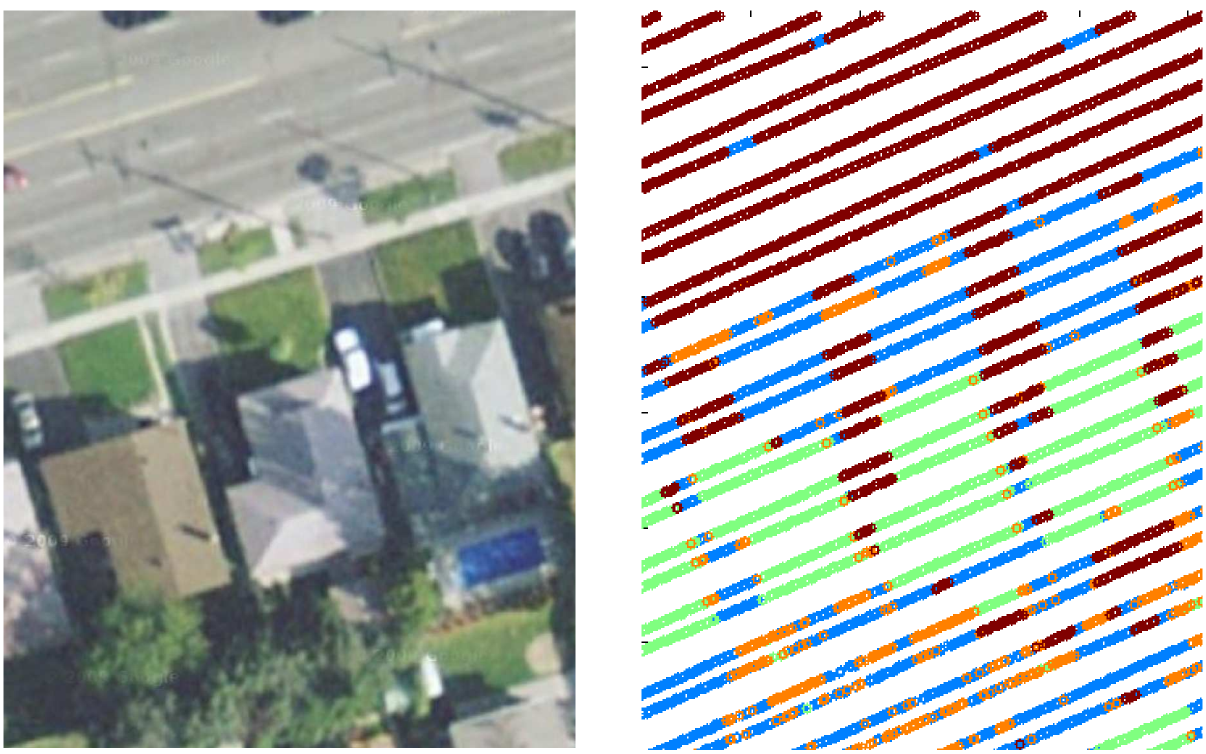

Figure 4. Gaussian function-based waveform reconstruction (Scarborough data set).

Fig. 4 provides a visualization of area and the waveform classification. Table 3 shows the results of the classification; the rows show the original categories, the columns show the categories after decompression. The sum of the percentages in the diagonal is 90.3%, slightly better classification results compared to the previous experiments, though the comparison is approximate as there was a minor difference in the two areas. The classification of 9.7% of the waveforms was affected by the compression method. The impact of compression is significant in the case trees, as 8.8% of the tree waveforms wer recognized as grass.

Table 3. Effect of the compression on the classification.

	Grass	Tree	Roof	Pavement
Grass	**21.6%**	0.4%	0.0%	0.7%
Tree	8.8%	**4.2%**	0.4%	0.0%
Roof	0.3%	0.3%	**25.6%**	0.1%
Pavement	1.9%	2.2%	0.0%	**33.5%**

CONCLUSIONS

Waveform processing is expected to become an integral part of LiDAR mapping, as the indications are that it can potentially improve the point cloud accuracy and can provide support for land cover classification and object identification. This initial study looked into the aspect using the compressed waveform domain for feature extraction, more specifically, classifying the object space into major categories, such as road, roof, grass and trees. Experiments with two data sets indicated that waveform can be efficiently compressed and classification in the compressed domain, based on an unsupervised method (SOM), is feasible. The preliminary results showed good performance for a typical residential area, where classification performance reached 90%.

ACKNOWLEDGEMENT

The authors thank Optech International and Woolpert for providing the data for this research.

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