COMPRESSING LIDAR WAVEFORM DATA

Sandor Laky[1,2], Piroska Zaletnyik[1,2], Charles Toth[1]

[1] Budapest University of Technology and Economics, HAS-BME Research Group for Physical Geodesy and Geodynamics, Muegyetem rkp. 3. Kmf. 16., Budapest, H-1111, Hungary, email: laky.sandor@freemail.hu, zaletnyikp@gmail.com

[2] The Ohio State University, The Center for Mapping, 470 Hitchcock Hall, 2070 Neil Avenue, Columbus, OH 43210, United States, toth@cfm.ohio-state.edu

ABSTRACT

Most commercial LiDAR systems temporarily record the entire laser pulse echo signal as a function of time to extract the return pulses at data acquisition level in real-time; typically up to 4-5 returns. Thus, adding sufficient data storage capabilities, the waveform data can be easily made available to users, providing the possibility of further analyzing the waveform and, thus, obtaining additional information about the reflecting object and its geometric and physical characteristics. However, the considerable size of the captured waveform data is enormous and currently not practical. The objective is to reduce the size of waveform data for faster transmission, for reduced storage requirements and to support feature extraction processing in general.

In this paper, the feasibility of compressing the waveform signal in a lossy way, such as wavelet transformation, is investigated. Additionally, the possibility of further compressing the signal by applying compressive sampling technique is analyzed.

Keywords: LiDAR, full-waveform, wavelet-based compression, compressive sampling

INTRODUCTION

Airborne LiDAR (also mentioned as airborne laser scanning (ALS)) is used in many areas nowadays such as digital elevation model (DEM) generation, 3D city modeling (Rottensteiner *et al*., 2005), metrology (Fidera *et al*., 2004), forest parameters estimation (Andersen *et al*., 2005), bridge and power line detection (Sithole and Vosselman, 2006), corridor, coastal mapping (Irish and Lillycrop, 1999) and also vertical object detection in aviation (Parrish, 2007).

The first commercially available airborne laser scanners provided only one backscattered echo per emitted pulse, later they could measure the first echo of the backscattered signal (first pulse) and the last echo (last pulse) (Shan and Toth, 2009). Multi-echo or multiple pulse laser scanning systems are able to measure up to six pulses. During the last decade, a new generation of airborne laser scanners appeared that are able to digitize and record the entire backscattered signal of each emitted pulse. They are called full-waveform (FW) LiDAR systems (Mallet and Bretar, 2009).

The full-waveform LiDAR technology provides the possibility of further analyzing the waveform and, thus, obtaining additional information about the reflecting object and its geometric and physical characteristics. Thus, adding sufficient data storage capabilities to the system, the waveform data can be easily made available to users. However, the considerable size of the captured waveform data is enormous and currently not practical. The objective is to reduce the size of waveform data for faster transmission, for reduced storage requirements, providing the possibility of acquiring more geospatial data with the same sensor hardware, and to support feature extraction processing in general.

In this paper we examine some compression techniques to reduce effectively the amount of waveform data. The used LiDAR dataset is from Ontario, collected from a residential area of Scarborough (Toronto) by an Optech ALTM 3100 full-waveform LiDAR system. The sample interval of the digitizer is 1 nanosecond, and at the maximum acquisition and recording rate of 50 kHz the maximum return record length is 440 ns, acquired in 2 sections. The first section starts acquiring data when the first return pulse is detected and continues until the signal is no longer present (i.e., below the threshold). The first segment is maximum 220 ns long. The second section will not begin data acquisition until the signal again rises above a certain threshold. The waveforms are then stored in different segments together with their starting time positions. The captured signal is digitized by an 8-bit analog-to-digital converter, giving a dynamic range of 256:1 (Optech, 2005).

The measurement time was around 16 seconds and the dataset contains more than 800 000 waveforms. As the area is a suburban area different types of backscattered signals can be observed for trees, grass, roads, roofs. Some typical waveforms are illustrated in Figure 1.

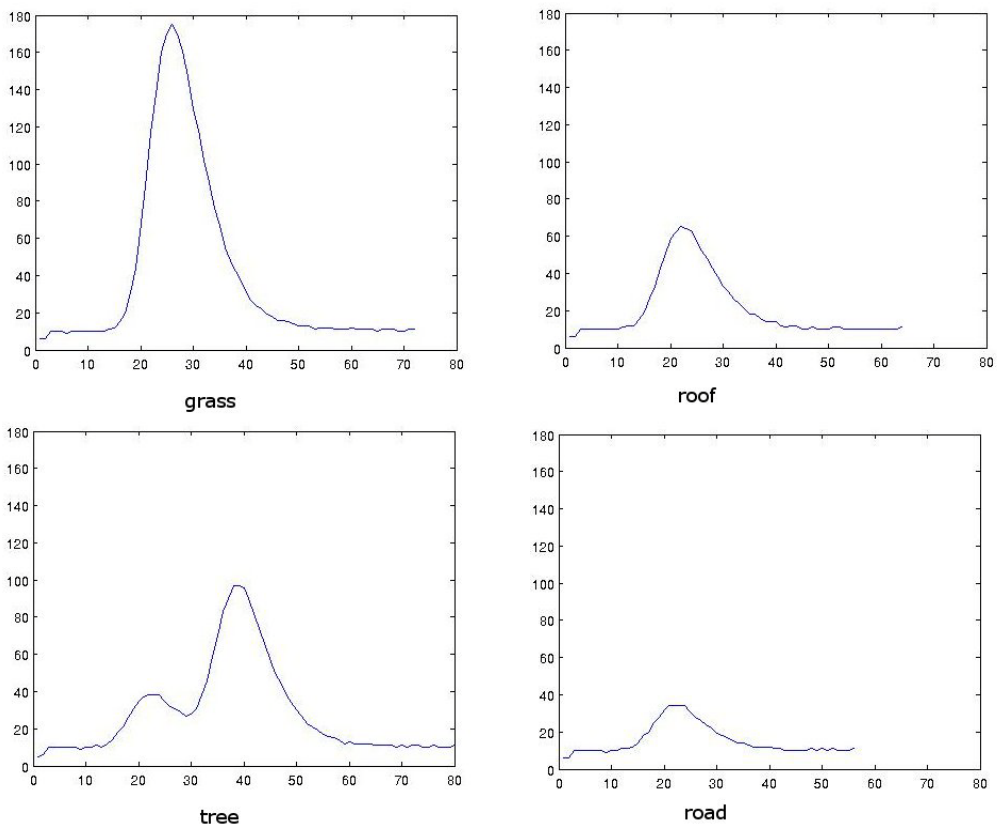

Figure 1 *Typical waveform types(x axis-time [ns] , y axis – intensity), (Courtesy of Optech Incorporated)*

The waveforms are stored in one (97.3%) or more (two or three) segments, with a maximum segment length of 220 ns. The compression methods are applied to these segments. For our study, 500 waveforms were representatively chosen from the dataset, proportional to the different pulse numbers of the waveforms. For this we used a pulse detection method to count the number of the pulses in the waveforms. The basic peak detection method is based on the zero crossings of the first derivative on the thresholded version of the waveform (Chauve *et al.,* 2007). In our method we used first a low pass filter to avoid the multiple close peaks caused by noise, and then the peaks were detected with the method reference above. In this Scarborough urban test area, 83.3% of the waveforms had one peak, 12.0% two, and 4.7% more peaks. This proportion is also maintained in the 500 chosen sample dataset.

COMPRESSION METHODS

Two main types of data compression method are the lossless and lossy compressions. With lossy methods better compression can be achieved, but the decompressed signal will not be identical to the original data. If the loss of data is small then the difference may not be perceptible in the case of image or sound compression. For LiDAR waveforms, 1-2 intensity value change is also acceptable, because it is below to the noise level of the signal.

The most general lossy compression techniques are the scalar quantization, vector quantization, differential encoding, transform coding (such as Karhunen-Loeve transform, Discrete Cosine Transform (DCT), Discrete Sine Transform, Discrete Walsh-Hadamart Transform), subband coding and wavelet-based compression.

In many compression techniques these methods are combined together, including lossless coding too. The basic encoding scheme in the case of transform coding is first to divide the source output into blocks, take the transform on this block, quantize the coefficients, and encode the quantized values. The DCT is one of the most popular transform coding techniques and is part of many international standards, such as JPEG or MPEG among others. However the transform coding techniques, such as JPEG, has the disadvantage of blocky appearance due to their encoding scheme. The wavelet-based coding, used in JPEG 2000 also, can correct this error and has higher compression efficiency (see Sayood, 2006).

Therefore, for the LiDAR waveform compression, we have chosen the wavelet-based compression with a quantization method and, additionally, the possibility of further compressing the signal by applying compressive sampling technique (see Candès and Wakin, 2008) was also examined.

WAVELET TRANSFORMATION

Wavelets were first applied in geophysics to analyze data from seismic surveys. Fourier transform is not a good tool here, because it gives only frequency information and it gives no direct information when the oscillation occurred. The short-time Fourier transform is better, where the full-time interval is divided into equal-time intervals. However, the equal-time intervals are not adjustable and therefore, it is hard to detect short duration high frequency events. Wavelets are better, they give also time and frequency information, and they can be used to “zoom in” or “zoom out” to detect high and low frequency spectral components also (Bogges and Narcowich, 2001).

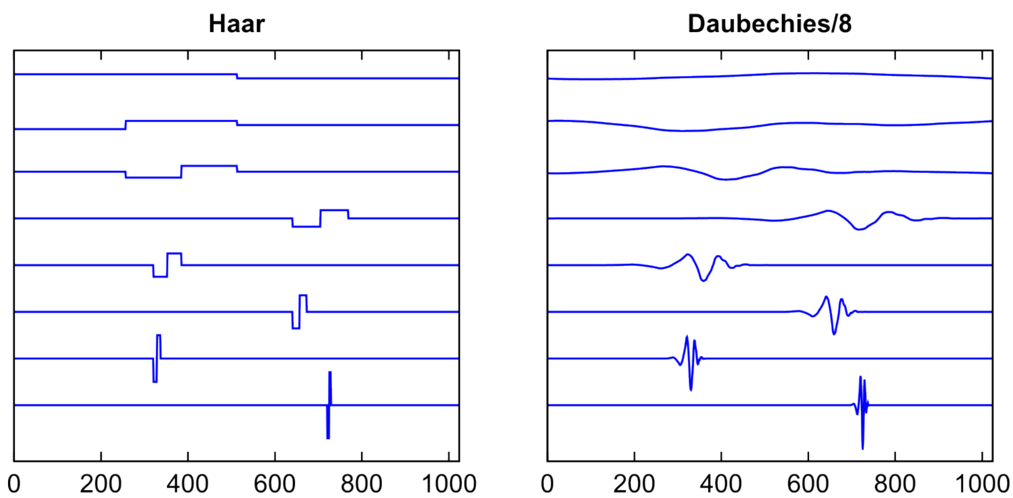

Figure 2 *Examples of Haar and Daubchies/8 wavelet basis functions*

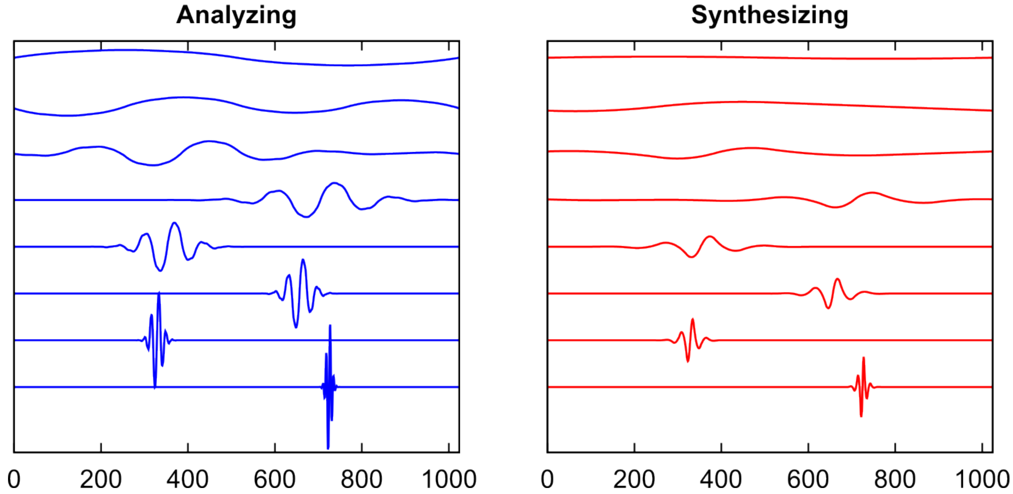

Figure 3 *Examples of CDF/3/9 analyzing and synthesizing basis functions*

In wavelet analysis two functions play a primary role, the scaling and the wavelet function. These two functions generate a family of functions that can be used to analyze the signal. A wavelet can be translated forward or backward in time, and stretched or compressed by scaling to obtain low and high frequency wavelets. The simplest wavelet is the Haar wavelet (Figure 2a). The Daubechies wavelets are a family of orthogonal wavelets having a high number of vanishing moments, thus used commonly in data compression (see Figure 2b). The name Daubechies is also associated with the biorthogonal CDF (Cohen-Daubechies-Feauveau) wavelet which is used in the JPEG 2000 standard. The biorthogonal wavelets has different analyzing and synthesizing wavelet functions (see Figure 3) in contrast to the traditional orthogonal wavelets where the same wavelet function is used for both analyzing and synthesizing the data.

As these are commonly used wavelets in data compression, we examined them to compress the LiDAR waveforms. Symmlet wavelets were also tried, which are as symmetrical as possible, compared to the Daubechies filters which are highly asymmetrical.

Figure 4 shows a typical LiDAR waveform and its wavelets coefficients (WCs), using the biorthogonal CDF wavelets. As can be seen in the figure, there are many small or zero coefficients, it is a very sparse signal. The small coefficients represent unimportant features, so discarding these coefficients can lead to a lossy compression which is both efficient and high quality.

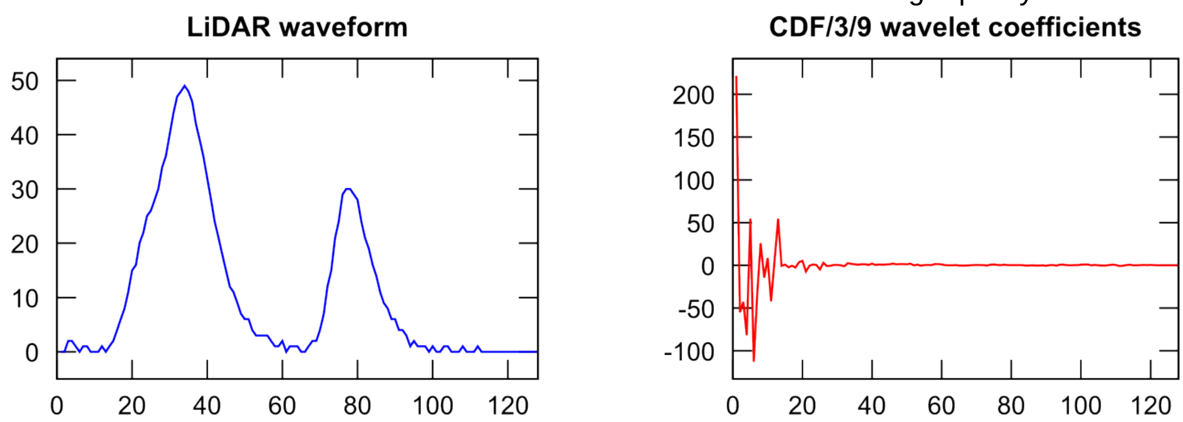

Figure 4 *Typical LiDAR waveform and its wavelet coefficients*

COMPRESSIVE SAMPLING

Given a signal f of length n, and a representation basis (for example, a matrix with wavelet basis functions as column vectors, thus being orthonormal) $\boldsymbol{\Psi}$ of size $n \times n$, we can calculate the coefficient vector x of f, and knowing the coefficient sequence, we can calculate the original signal again:

$$x = \boldsymbol{\Psi}^{T} \cdot f \quad \leftrightarrow \quad f = \boldsymbol{\Psi} \cdot x \ .$$

We can calculate the s-sparse version of x (x_S), by zeroing out all but the s largest coefficients. If the representation x is fundamentally sparse (i.e. it has (n-s) coefficients close enough to zero), the approximating signal f_S calculated from x_S differs minimally from the original signal (this is the basic idea of the wavelet compression discussed in the previous section).

Let $\boldsymbol{\Phi}$ represent an other basis, the sensing basis. Matrix $\boldsymbol{R}$ is a selection matrix of size $m \times n$ (i.e. it is a set of m random rows of an identity matrix), where m is the number of the measurements we want to keep. Let y be the measurement vector of size m, calculated as:

$$y = \boldsymbol{R} \cdot \boldsymbol{\Phi} \cdot f \ .$$

If the number of measurements we keep, m, is significantly smaller than the length of the signal, n, we can talk about compressive sampling (Candès and Wakin, 2008, Baraniuk, 2007). Speaking about x being itself a sparse signal, the compressive sampling can be reduced to

$$y = \boldsymbol{R} \cdot \boldsymbol{\Phi} \cdot \boldsymbol{\Psi} \cdot x = \boldsymbol{A} \cdot x \ ,$$

with $\boldsymbol{A}$ ($m \times n$) being the measurement matrix. The question is: what guarantees that the original signal can be recovered from the measurement vector? It has been studied before that random matrices, e.g. matrices with independent identically distributed Gaussian elements obey the Restricted Isometry Property, which makes them near-optimal measurement matrices.

The process of finding the signal f knowing y, $\boldsymbol{A}$ and $\boldsymbol{\Psi}$ can be regarded as an optimization problem of the form

$$\min \| x_E \|_{\ell 0} \ \text{subject to}$$
$$\| \boldsymbol{A} \cdot x_E - y \|_{\ell 2} \rightarrow \min, \ f_E = \boldsymbol{\Psi} \cdot x_E$$

where x_E is the estimated coefficient vector and f_E is the estimated signal. This is an ℓ_0 optimization problem (the ℓ_0 norm of a vector is the number of its non-zero elements) with ℓ_2 restriction. Thus, we can say, we are seeking a sparse representation x_E of f in the representation basis $\boldsymbol{\Psi}$, which, when the sensing process is applied to, differs minimally (in the least squares sense) from the measurement vector. In our experiment, we will solve this problem using the Orthogonal Matching Pursuit algorithm (Tropp and Gilbert, 2007).

WAVEFORM COMPRESSION WITH WAVELETS

Compressing LiDAR waveforms with wavelets, the first question is to find the most appropriate wavelet function to the problem. Therefore we examined the compression performance of different wavelet families such as Haar, Daubechies, Symmlet and biorthogonal CDF wavelets with different parameters.

For the wavelet transformation we used the free Wavelab 850, which is a collection of Matlab functions to implement a variety of algorithms related to wavelet analysis. The wavelet transformation functions of Wavelab works with the power of two sequence length data, so the waveform data sequences were modified a little before the transformation, first they were reduced by 10 (as normally this is the lowest value of every waveform) and then filled with zeros until the nearest power of two to meet the sequence length condition.

Figure 5 shows the performance of the different wavelet families (from each wavelet family only the best is shown in the figure). The horizontal axis is the compression rate, which is defined here as the number of non-zero elements of the wavelet coefficient (WC) vector divided by the original length of the WC vector), and the vertical axis is the signal error, the difference (standard deviation or maximum absolute error) between the original and the reconstructed signal using different compression rates. Table 1. shows the standard deviation and maximum absolute value of signal error at given compression ratios. It can be seen from the data in Table 1. (and also in Figure 5) that the curve of the CDF wavelets is the less steep approaching the lowest compression ratios, thus the data can be compressed more effectively with this wavelet family then with the others. Therefore in the further investigations we used the CDF/3/9 wavelet.

Using CDF/3/9 wavelet, it is enough to store the first 32 wavelet coefficients, as from these WCs the original signal can be reconstructed near perfectly (the standard deviation of the differences is 0.5 intensity value). The mean waveform segment length is 76 and the intensity values are between 0-255, which means that one intensity value can be stored in 1 byte, so the mean waveform segment storage necessity is 76 bytes. Unfortunately, the waveform coefficients are not integer numbers between 0-255, but real numbers, and examining the wavelet coefficients for the 500 sample waveforms, they vary between -400 and 715. This means that to store the first 32 WCs more storage capacity is needed than the original signal (if we store the data as float numbers, each requires 4 byte). Therefore, to achieve real compression we need to reduce the size of the numbers. This is possible if we quantize the data.

Here we chose a uniform midtread quantizer with 256 levels (to store each wavelet coefficients also in 1 byte). Choosing midtread quantizer, where the reconstruction levels include the value of zero, the size of the wavelet coefficient vector can be reduced, so normally less then 32 WCs remain. The small coefficients representing unimportant features can be discarded by thresholding the wavelet coefficients (so the WCs vector size is further reduced, as the small values are normally at the end of the vector).

Figure 6 shows the effect of the quantization on the differences between the reconstructed and the original signal according to different threshold values. Figure 7 shows the effect of the quantization threshold on the compression performance, the compression rate is defined here as the quantized WCs vector length vs.original signal length.

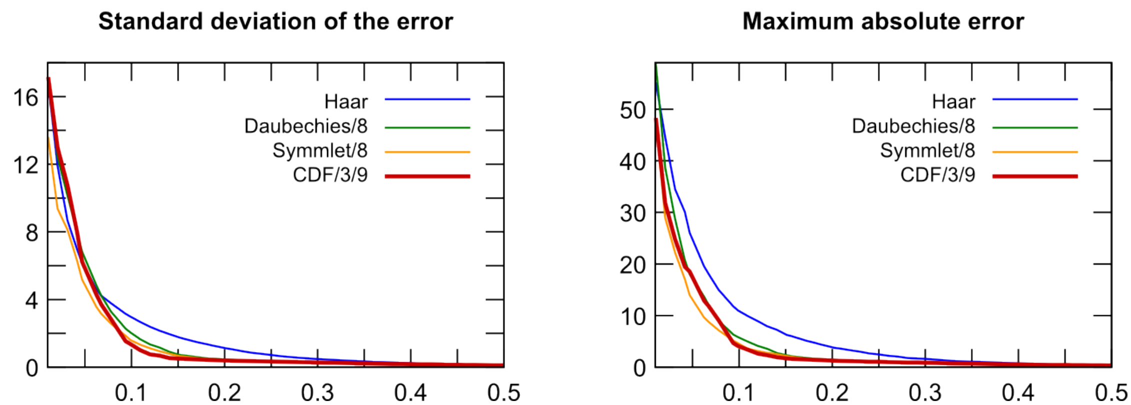

Figure 5 *Evaluation of different wavelet families with respect to compression performance*

Comp. rate	25%		20%		15%		10%		5%	
Family	Std	Max	Std	Max	Std	Max	Std	Max	Std	Max
Haar	2.49	0.72	3.88	1.14	6.36	1.79	10.88	2.95	24.77	5.78
Daubechies	1.01	0.34	1.44	0.46	2.38	0.74	5.74	2.01	17.16	6.32
Symmlet	1.02	0.34	1.39	0.44	2.19	0.67	4.52	1.57	13.13	4.70
CDF	1.05	0.33	1.29	0.40	1.71	0.50	4.02	1.34	17.43	5.54

Table 1 *Compression performance of different wavelet families*

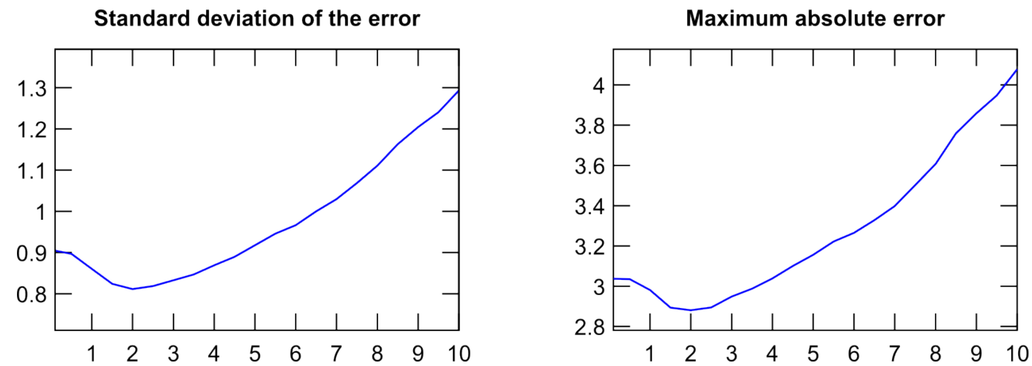

Figure 6 *Effect of wavelet coefficient (WC) quantization on the signal as a function of quantization threshold*

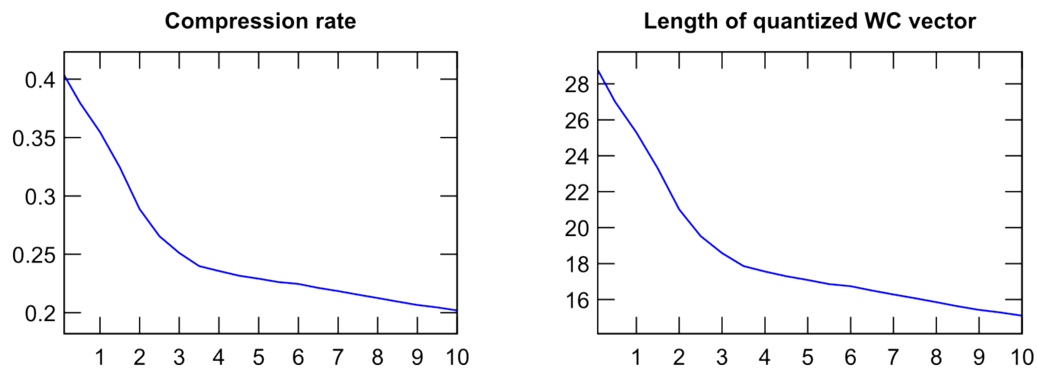

Figure 7 *Compression performance as a function of quantization threshold*

Quantization threshold	Mean signal error	Std of signal error	Max. absolute value of signal error	Mean compression rate
0.1	-0.01	0.90	3.04	40%
1.0	-0.00	0.86	2.98	35%
3.0	0.01	0.83	2.95	25%
5.0	0.01	0.92	3.16	23%
7.0	0.02	1.03	3.40	22%
10.0	0.02	1.29	4.08	20%

Table 2 *Signal errors and compression rate after quantizing the wavelet coefficients (compression rate = quantized WC vector length/original signal length)*

In Table 2, we can find the mean signal error, standard deviation error, the maximum absolute error of the signal and the mean compression rate according to some threshold values. In the developed compression method, we have chosen 5 for threshold value, as the standard deviation of the signal is still less than 1 intensity value, and the achieved compression rate is 23% (with 0.1 threshold it was only 40%).

Figure 8 shows an example for the original and reconstructed signals and the signal error with CDF wavelet transformation, using midtread quantization with 5 quantization threshold. In this example, the achieved compression was 23.1%, when only 24 wavelet coefficients were strored instead of the 104 original signal components. Figure 9 shows the quantization error on the wavelet coefficients for the same waveform.

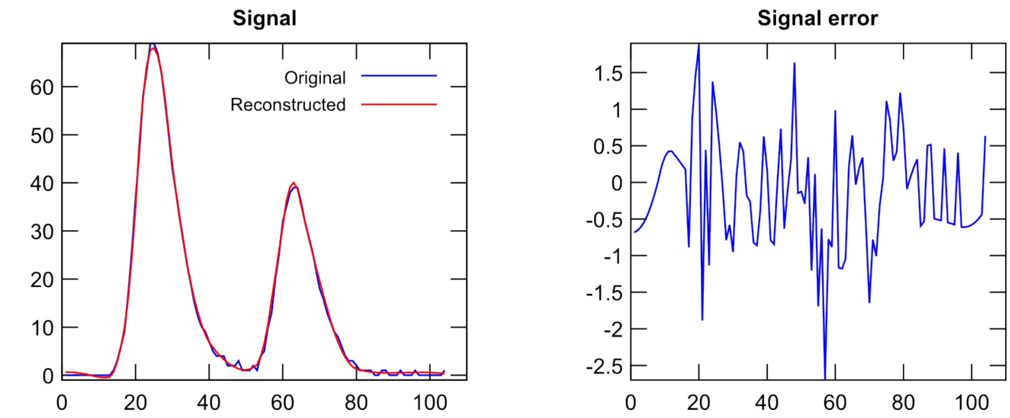

***Figure 8** Example of the effect of wavelet coefficient quantization on one signal (threshold=5.0, length of quantized wavelet coefficient vector=24, length of the original signal=104, compression rate=23.1%)*

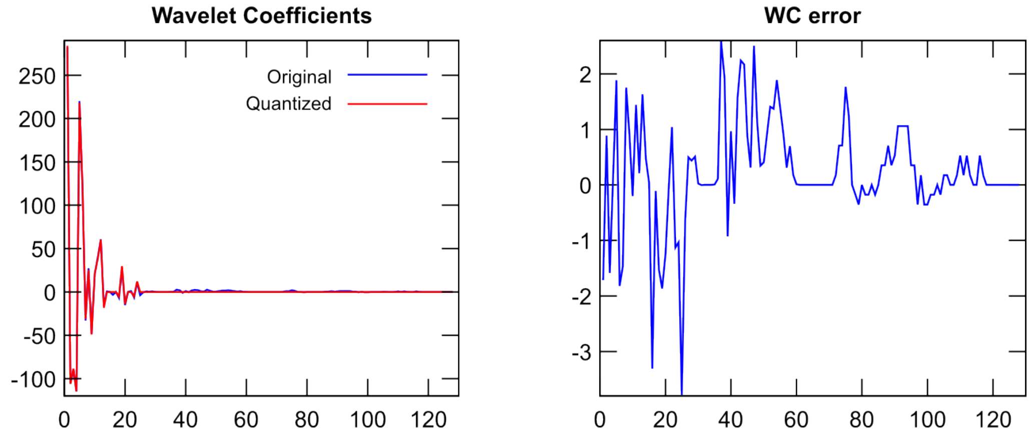

***Figure 9** Example of the effect of the quantization error on the wavelet coefficients (threshold=5.0, length of quantized wavelet coefficient vector=24)*

WAVEFORM COMPRESSION WITH COMPRESSIVE SAMPLING

Our initial experiments have showed that compressing single waveforms with compressive sampling is not efficient. Therefore, the wavelet coefficient quantization described in the previous chapter is recommended. We have tested the compressive sampling applied to a continuous stream of digitized waveforms, split to segment lengths of 1024. We have considered the CDF/3/9 wavelet transform coefficients of these segments as sparse signal vectors to be measured. In our test we have created 10 such segments, and each of those segments was compressed and then decompressed using 10 different measurement matrices created randomly with elements following the Gaussian distribution. The number of measurements (the length of the measurement vector) varied between 62 and 310 (these numbers were chosen based on the sparsity of the WC vectors). Thus, there were 100 experiments for every number of measurements. The measurement vector was stored at a precision of 1 byte.

The fundamental question is: how many measurements are needed to successfully reconstruct the waveforms? We have chosen two statistical properties of the signal error (the difference between the original and the compressed-and-decompressed signal) as the indicator of the success: (a) the maximum absolute value of the error should be under 10 intensity values, or (b) the standard deviation of the error should be under 1 intensity value. The values of these statistics are shown in Figure 10, as a function of the number of measurements.

Let us consider only the 33 most successful experiments out of the 100 performed at every measurement number. As shown in Figure 11, the probability of the successful recovery (which is the ratio of the successful recoveries compared to the number of experiments) is ~1 with approximately 250 measurements, which means a compression ratio of about 0.24. What the figures also show us, that the dispersion of the statistics is quite large (especially when taking into account not just the 33 most successful experiments). This implies that choosing the right measurement matrix is extremely important to achieve high recovery probability.

One way of achieving better performance would be the optimization of the measurement matrix (Elad, 2007). An other way could be choosing a more suitable optimization algorithm. In our test, we have used the Orthogonal Matching Pursuit (OMP). Two other methods (Basis Pursuit via linear programming and via evolutionary algorithm) have been evaluated, but their performance was below the performance of OMP (the cause should be further investigated).

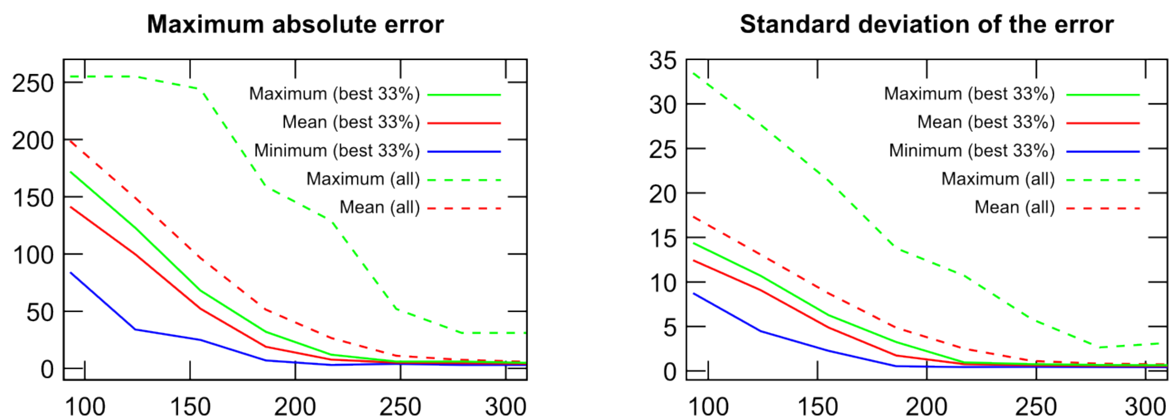

Figure 10 *Maximum absolute recovery error and standard deviation of the recovery error as a function of the number of measurements*

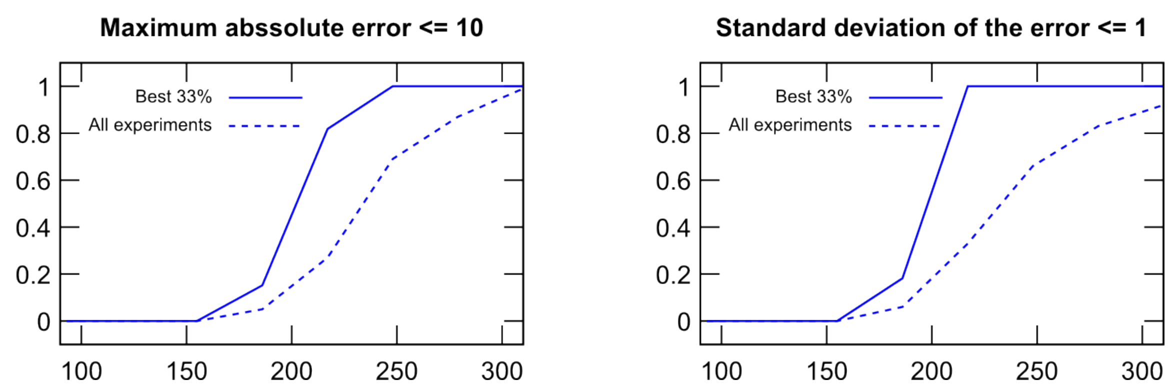

Figure 11 *Probability of successful recovery as a function of the number of measurements*

SUMMARY

In this study we examined different compression techniques to reduce the size of the LiDAR full-waveform for faster transmission, for reduced storage requirements and to support feature extraction processing in general.

Two compression methods were applied, the wavelet-based compression and the compressive sampling technique.

The effectiveness of different wavelet families were examined for the wavelet-based compression of the waveforms and, finally, the biorthogonal CDF/3/9 was chosen with the best compression rates for this problem. The wavelet coefficients were thresholded first (with a value of 5) to discard the small coefficients representing unimportant features, and then a uniform midtread quantizer with 256 levels was applied to the data. With this method a 23% compression rate was achieved, so the data was compressed to less then one quarter of the original size, with only 1 intensity value of standard deviation between the original and the reconstructed signal.

The compressive sampling is a new promising compression technique. Our initial experiments showed that compressing single waveforms with compressive sampling is not efficient, though applying them on a continuous stream of digitized waveforms may work effectively. The experiments have shown that the efficiency of compressive sampling is highly dependent on the chosen measurement matrix. In this study a compression rate about of 24% was achieved (the same level, as with wavelet-based compression), but with optimized measurement matrix, or choosing a more suitable optimization algorithm, the performance can be increased.

ACKNOWLEDGEMENT

The authors thank to Optech Incorporated for the data provided for this research.

REFERENCES

Andersen, H.-E., McGaughey, R., Reutebuch, S., 2005. Estimating forest canopy fuel parameters using LIDAR data. Remote Sensing of Environment 94 (6), 441_449.

Baraniuk, R. G., 2007. Compressive Sensing [Lecture Notes]. IEEE Signal Processing Magazine, 24 (4), pp. 118-121

Bogges, A., Narcowich, F. J., 2001. A First Course in Wavelets with Fourier Analysis, Prentice Hall, Upper Saddle River, New Jersey, 283 pages

Candès, E. J., Wakin, M. B., 2008. An Introduction To Compressive Sampling, IEEE Signal Processing Magazine, 25 (2). pp. 21-30.

Chauve, A., Mallet, C., Bretar, F., Durrieu, S., Pierrot-Deseilligny, M., Puech, W., 2007. Processing full-waveform LiDAR data: Modelling raw signals. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 36 (Part 3/W52), pp. 102-107.

Elad, M., 2007. Optimized Projections for Compressed Sensing. IEEE Transactions on Signal Processing, 55 (12), pp. 5695-5702

Fidera, A., Chapman, M., Hong, J., 2004. Terrestrial LiDAR for industrial metrology applications: Modelling, enhancement and reconstruction. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 35 (Part B5), pp. 880-883.

Irish, J., Lillycrop, W., 1999. Scanning laser mapping of the coastal zone: The SHOALS system. ISPRS Journal of Photogrammetry & Remote Sensing 54 (2_3), pp. 123-129.

Mallet, C., Bretar, F., 2009. Full-waveform topographic LiDAR: State-of-the-art, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 64, Issue 1, pp. 1-16.

Optech Incorporated, 2005. Airborne Laser Terrain Mapper (ALTM) Waveform Digitizer Manual, Optech Incorporated, Toronto, Ontario, Canada, Document No. 0028443/Rev A.5

Parrish, C. E., 2007. Exploiting full-waveform LiDAR data and multiresolution wavelet analysis for vertical object detection and recognition, Geoscience and Remote Sensing Symposium, 2007. IGARSS 2007. IEEE International, pp. 2499-2502.

Rottensteiner, F.; Trinder, J.; Clode, S., 2005. Data acquisition for 3D city models from LIDAR extracting buildings and roads, Geoscience and Remote Sensing Symposium, 2005. IGARSS '05. Proceedings. 2005 IEEE International, Volume 1, pp. 521-524.

Sayood, K. 2006. Introduction to Data Compression, Third Edition (Morgan Kaufmann Series in Multimedia Information and Systems), Elsevier, San Francisco, 680 pages

Shan, J., and Toth, C. K., 2009. Topographic Laser Ranging and Scanning—Principles and Processing, CRC Press Taylor & Francis, London, 590 pp.

Sithole, G., Vosselman, G., 2006. Bridge detection in airborne laser scanner data. ISPRS Journal of Photogrammetry & Remote Sensing 61 (1), pp. 33-46.

Tropp, J. A., Gilbert, A. C., 2007. Signal Recovery from Random Measurements via Orthogonal Matching Pursuit, IEEE Transactions on Information Theory, 53 (12), pp. 4655-4666