**PFG 2015 / 3, 0201 – 0213**
Stuttgart, June 2015

**Article**

# Study on Sensor Level LiDAR Waveform Data Compression Using JPEG-2000 Standard Multi-Component Transform

Grzegorz Jóźków, Charles Toth, Columbus, OH, USA, Mihaela Quirk, Washington D.C., USA & Dorota Grejner-Brzezinska, Columbus, OH, USA

**Keywords:** LiDAR, full-waveform, compression, JPEG-2000 Standard, decorrelation, performance analysis

**Summary:** In contrast to LiDAR data provided by discrete return systems, full waveform LiDAR data (FWD) improve the quality of products and extend the possibilities of their application. Beside evident benefits, FWD imposes strong requirements on the sensor acquisition and storage hardware. At the moment, there is little effort reported on sensor level waveform data compression. Vendor specified waveform data formats are generally not published for the users and do not mention compression options. Since the recorded waveform is intrinsically noisy, there is less practical need to use lossless compression methods. As long as the properties of FWD are preserved, in other words, as long as it is possible to extract the same FWD features, and the compression noise is below or comparable to the noise of the signal, lossy compression methods are suitable. Such compression of FWD was studied in previous work where waveforms were compressed individually or in groups forming images, which is considered as 1D and 2D compression, respectively. This work presents a strategy for FWD compression that is based on multi-component transforms, which is included in JPEG-2000 Standard Part 2. This extension to JPEG-2000 Standard exploits the 3D correlation between waveform samples and allows compressing waveform cubes without organizing samples. The results of this study indicate that the removal of data redundancies in all three dimensions results in slightly better compression performance than using 1D or 2D approaches. More importantly, the user has the flexibility to decide on how much the data should be compressed or what level of the reconstruction error is allowed. Besides JPEG-2000 compression, this investigation includes experiments with additional data decorrelators, such as Karhunen-Loève transform and wavelet transform. The conclusion of this study is that the JPEG-2000 Standard is an effective method for FWD compression of waveform cubes, resulting in high compression ratios and low data degradation.

**Zusammenfassung:** *Untersuchung zur Kompression von Full Waveform LiDAR-Daten auf Sensorebene unter Verwendung der JPEG-2000 Multikomponenten-Transformation.* Im Gegensatz zu den üblichen Discrete Return Systemen können Full Waveform LiDAR-Daten (FWD) die Qualität der Produkte verbessern und erweitern somit ihre Anwendungsmöglichkeiten. Neben diesen offensichtlichen Vorteilen stellen FWD sehr hohe Anforderungen an den Sensoraufbau und die verfügbare Speicherkapazität. Bisher gibt es noch wenige Arbeiten zur Datenkompression der FWD-Daten auf Sensorebene. Herstellerspezifische Full Waveform Datenformate werden in aller Regel nicht dem Anwender zur Verfügung gestellt und erwähnen keine Möglichkeit der Datenkompression. Da die aufgezeichneten FWD ohnehin verrauscht sind, ist es nicht nötig, eine verlustfreie Kompression zu verwenden. Solange die Eigenschaften der FWD erhalten bleiben, das heißt, dieselben FWD-Merkmale extrahiert werden können und das Kompressionsrauschen unter oder vergleichbar dem Signalrauschen ist, können auch verlustbehaftete Kompressionsmethoden genutzt werden. Diese Art der FWD-Kompression ist aus vorherigen Studien als 1D- oder 2D-Kompression bekannt, bei denen einzelne oder Gruppen von Wellenformen als Bilder interpretiert und komprimiert werden. In dieser Arbeit wird eine Strategie zur FWD-Kompression präsentiert, welche auf einer Multikomponenten-Transformation basiert und im JPEG-2000 Standard Teil 2 beschrieben ist. Diese ist eine Erweiterung zum JPEG-2000-Standard, die die 3D-Korrelation zwischen Waveform-Proben auswertet und damit die Kompression eines kompletten Waveform-Kubus ohne Proben als Startwerte erlaubt. Die Ergebnisse dieser Studie zeigen, dass das Entfernen von Redundanzen in allen drei Dimensionen zu einer geringfügig besseren Kompression als die ausschließliche Nutzung von 1D- oder 2D-Informationen führt. Zusätzlich eröffnet sich dem Nutzer jedoch die Möglichkeit zu entscheiden, wie


DOI: 10.1127/pfg/2015/0265 1432-8364/15/0265 $ 3.50

stark die Daten komprimiert werden sollen oder welcher maximale Fehler bei der Rekonstruktion zugelassen wird. Neben der JPEG-2000-Kompression beinhaltet unsere Untersuchung Experimente mit zusätzlicher Datendekorrelation wie der Karhunen-Loève-Transformation und der Wavelet-Transformation. Das Ergebnis dieser Studie zeigt, dass der JPEG-2000-Standard eine effektive Methode für FWD-Kompression in Form eines Waveform-Kubus bietet. Daraus resultiert eine hohe Kompressionsrate bei nur geringem Qualitätsverlust der Daten.

## 1 Introduction

The hardware developments of laser scanning technology continuously provide new application possibilities, though, limitations and difficulties are frequently encountered in the introduction phase. Starting from 2004, when the full-waveform digitization became available for the commercial airborne scanning systems (Hug et al. 2004, Mallet & Bretar 2009), improvements of quality of LiDAR data and products have been observed. The main advantages of the full waveform data (FWD) are: (1) denser and more accurate point cloud generation (Mallet & Bretar 2009, Parrish & Nowak 2009), (2) improved results in vegetation mapping, e.g. for forestry applications (Pirotti 2011), and (3) better point cloud classification (Reitberger et al. 2008, Toth et al. 2010, Heinzel & Koch 2011, Mallet et al. 2011). Despite of the advantages of FWD, technology limitations are still present. For example, waveform data may not be recorded at maximum pulse rate designated for the discrete return systems; there is also a lack of vendor independent tools for waveform data processing; finally, the most common problem is the amount of FWD. Typically, FWD binary files, e.g. Riegl SDF, are 3–4 times larger than the binary files (LAS) containing corresponding point clouds. Although storage technologies continue to develop, allowing for faster read/write operation and accommodation of larger data volumes, the drawback of the increasing size of FWD continues to be an issue.

Most of the activities of LiDAR data compression are concerned with the reduction of the point cloud size to better support the dissemination of primary LiDAR products. The most widely used solutions in practice are the lossless LASzip (Isenburg 2011), LASCompression (GeMMA Lab 2009, Mongus & Žalik 2011) and the lossy/lossless LiDAR Compressor (Lizardtech 2014). Other approaches are hardware accelerated compression (Biasizzo & Novak 2013) or considering the point cloud thinning as lossy compression in topographic applications (Pradhan et al. 2005). Although the need for FWD compression is indisputable, there is rather limited research related to sensor level waveform compression. Work on compressing each waveform separately (Toth et al. 2010) and exploiting 2D correlation between waveform samples for more efficient compression is reported in Jóźków et al. (2015). Bunting et al. (2013) proposed the Sorted Pulse Data (SPD) format for storing LiDAR data, implemented in the open source software library SPDLib (SPDlib 2013). SPD follows the Hierarchical Data Format version 5.0 (HDF5) (Koranne 2011, The HDF Group 2014) which supports lossless compression using the zlib deflate algorithm (The Internet Engineering Task Force (IETF) 1996). Since this compression does not exploit LiDAR data properties, e.g. spatial or temporal correlation, the compression ratio is likely to be limited. Due to the complexity of data stored in SPD, it is difficult to compare the compression ratios with those obtained using other methods. Though there are results reported on SPD file compression, they are based on limited experiments (Bunting et al. 2013). Another proposed waveform exchange standard, PulseWaves (Isenburg 2014) provides an option for file compression, but it is still in the development phase, so details are unknown at the moment. Additionally, waveform decomposition for a sum of components or echoes (Chauve et al. 2007, Mallet & Bretar 2009) also represents lossy FWD compression allowing for reconstruction/decompression. Obviously, the compression rate and data distortion strongly depend on the number of detected echoes. According to the authors' knowledge, there is no work published assessing the performance in terms of ratio and reconstruction noise of the lossy compression represented by waveform decomposition parameters.

Since there is little need for lossless compression of FWD (Jóźków et al. 2015), this paper investigates a lossy compression approach which employs the extensions of JPEG-2000 Standard Part 2 of multi-component transform. This transform allows exploiting the correlation of waveform samples along three directions: waveform, scan line, flight line, and then compresses the entire waveform cube without the need of separating and compressing single waveforms or arranging them into groups, etc. In relation to 1D (Toth et al. 2010), and 2D (Jóźków et al. 2015) compression of FWD, the expected gain of the approach proposed here is a higher compression ratio, as the data redundancy may be better removed by considering full spatial (3D) correlation of the waveforms. Additionally, two other transforms for FWD decorrelation were tested to investigate whether the reported high performance of compression based on JPEG-2000 Standard could be further improved.

## 2 Waveform Data Arrangement

### 2.1 *Waveform Cube*

Full waveform data is not necessarily restricted to the digitized waveform, but is usually identified with waveform signal samples, the essential data for further processing. Additional data, such as time and pointers to flight navigation parameters are necessary to compute geolocation and, finally, to create the point cloud. The size of the mandatory metadata, however, is much smaller than the size of waveform samples, which implies that the compression is mainly considered for waveform samples. Besides the vendor specified formats for waveform data storage, which are usually unknown, there are independent standards allowing the waveform data exchange, such as the LAS format (ASPRS 2013); note that only point data record formats starting from LAS v1.3 are able to store FWD, and the PulseWaves tool (Isenburg 2014) or SPDLib (SPDlib 2013) have this capacity, too. The strategy used in the approach proposed here for waveforms compression is based on a 3D waveform data structure, called a waveform cube (Jóźków et al. 2015), due to its similarity to the image cube of hyper-spectral images. A very similar idea of representing waveforms in a volumetric data structure, but for static terrestrial scanning, was presented earlier by Stilla & Jutzi (2008). The waveform cube is not a standard or a file format, but the structure of FWD arrangement that maintains the topology of waveform samples according to the data acquisition process (Fig. 1). The three dimensions of the waveform cube are: flight direction of the aircraft, scan line (cross flight direction), and the direction of the laser pulse propagation (waveform). It must be emphasized that the waveform cube is not a georeferenced structure, such as an orthophoto or a digital terrain model (DTM) grid, i.e. the distance in the 3D space between any two elements of the cube cannot be calculated based in the cube indices; however, the topology of waveform samples is always related to the spatial order of the laser pulses, i.e. the sequence, as they are acquired in time.

While the formation of the waveform cube is simple, there are a few additional aspects that should be mentioned. First, the outgoing pulse is also digitized as part of the waveform record, since this information is essential for waveform decomposition. There are two ways to compress the outgoing waveform: either jointly with the return waveform or independently, by forming another waveform

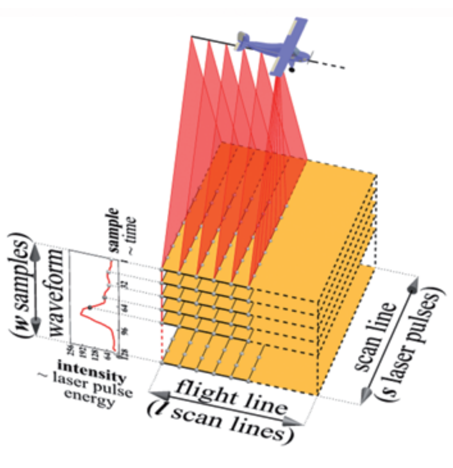
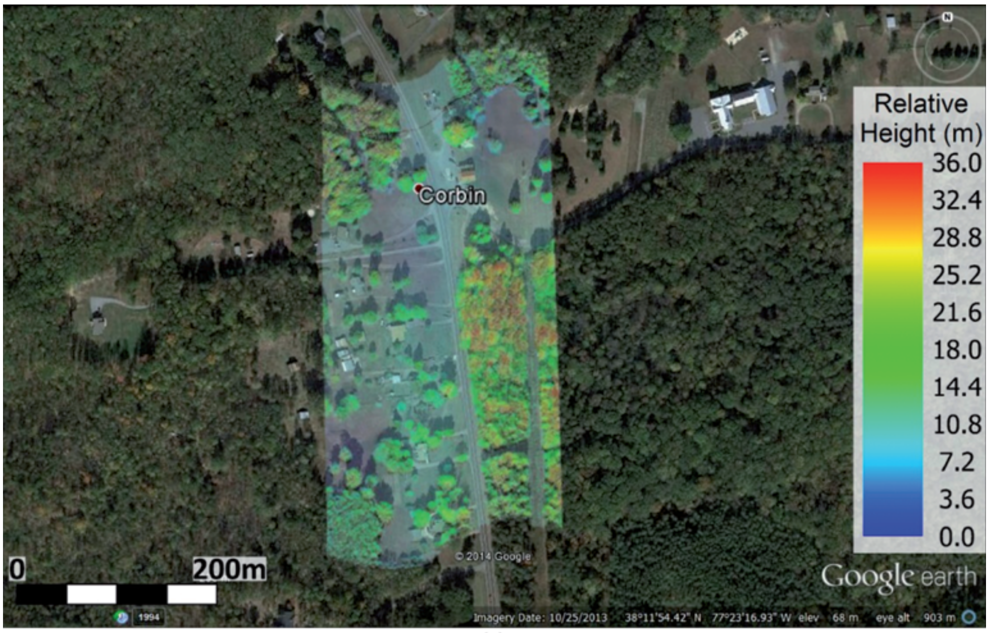


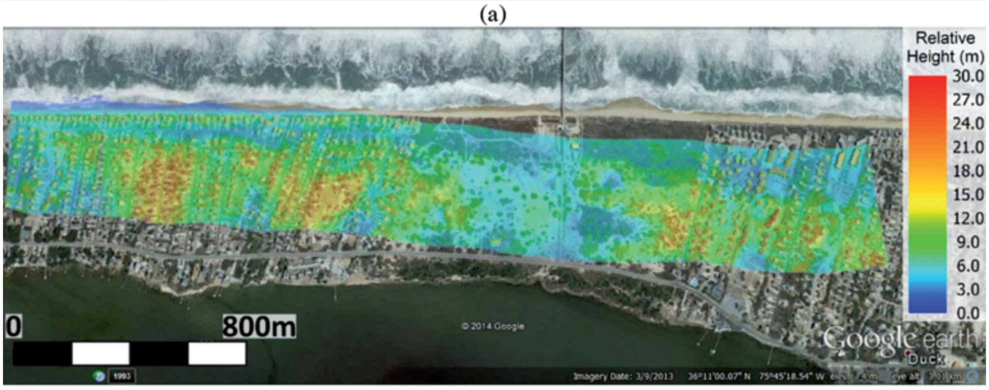

**Fig. 1:** Waveform cube structure.

cube. Since the size of the outgoing waveform is fixed, the second option is preferred. Similarly, for multi-wavelength LiDAR systems, waveform cubes can be formed for each sensor; note the correlation among the different wavelength waveform could be potentially exploited for compression in the future. The second aspect is the object space complexity, which has a paramount effect on the spatial correlation of the waveforms. Neighbouring waveforms are generally similar to each other over open and slowly changing areas, whereas in built-up areas, such as urban canyons, their shape can change abruptly, resulting in a less efficient compression.

The third aspect is the waveform cube size which is defined in two directions by the waveform record length and the number of pulses per scan line. Both may fluctuate on some systems, in which case, empty waveform samples or records can be inserted, respectively. The third dimension, however, can be set arbitrarily, ranging from a few scan lines to all the scan lines in a strip. Given the spatial extent and the computational aspects, a nearly equal size in the horizontal dimensions is preferred,




(a)




(b)

**Fig. 2:** Test waveform cube location: (a) Area covered by both the C1 and C2 cubes, Corbin, Virginia, USA, (b) C3 cube, Duck, North Carolina, USA.

which is similar to the standard practice of tiling large geospatial data. Note that some sensors use multiple waveform digitizers, requiring the use of multiple cubes.

In summary, the idea of the waveform cube is not ideal in terms of implementation, as it may not be directly applicable to all scanners; for example, waveform sample rearrangement may be needed. Yet in a statistical sense, the waveform cube provides an effective way to achieve high compression performance due to its ability to exploit 3D correlation.

### 2.2 *Test Data*

The data variability greatly affects compression performance manifested by the value of the compression ratio; usually data with a low variation can be compressed with higher ratio than more varying data. Consequently, test data for the assessment of compression performance should be chosen carefully, avoiding the extreme conditions of high and low data complexity. The test site, shown in Fig. 2a, contains a mixture of topographic elements, such as buildings, road infrastructure, dense forest, single trees, and open terrain. To support this study, two waveform cubes were extracted and used in extensive tests, covering nearly the same area and acquired by using two different LiDAR systems (Riegl Q680i and Riegl Q780) on the same flight. This explains a slightly different size of both test waveform cubes of 504 × 1200 × 120 and 488 × 1170 × 120 scan lines, waveforms per scan line, and samples in the waveform (*l, s, w* dimensions in Fig. 1), for the first (C1) and the second (C2) cube, respectively. Additionally, a 3 km single strip, C3 (Fig. 2b), acquired using a Riegl Q780 scanner, was processed, allowing to test the algorithm in diverse conditions, in terms of topographical objects. Tests for C3 data included both emitted and returned waveform cubes; the numbers of waveform samples were 28 and 120, respectively. The strip was divided into 12 cubes, each containing 496 scan lines, and the number of pulses was 1170 per scan line.

For all datasets, the signal intensity was sampled at 1 ns with 8 bit resolution. Thus, the waveform consisting of 120 samples represent a vertical range of 36 m, clearly sufficient to include all the natural and man-made objects in these areas.

## 3 Compression Strategy

Similarly to our previous work, only lossy compression methods were considered because a perfect reconstruction of recorded FWD is practically not necessary, as discussed in details by Jóźków et al. (2015). Based on those results, it was concluded that JPEG-2000 Standard was the most efficient among the tested 2D strategies of waveform data compression. Here the objective is to extend the compression from 2D to 3D, so the goal of this study is to benefit waveform data compression by exploiting the correlation of waveform samples in each of three dimensions: along flight line, scan line, and waveform direction. Extensions of the JPEG-2000 Part 2 (Taubman & Marcellin 2002) introduce a multi-component transform resulting in the ability to compress multi-band images. In short, the simplest multi-component transform first applies a decorrelating transform, e.g. 1D wavelet transform, to each pixel of the image in the third dimension, and then each image component, e.g. band, follows the JPEG-2000 Part 1 compression schema. Due to the Part 2 extension, previous JPEG-2000 restrictions of compression only single band or three band images, as RGB, were removed and the possibility of applying JPEG-2000 compression to hyper-spectral images consisting of multiple bands became available (Kulkarni et al. 2006). Since the structure of hyper-spectral images and waveform cubes are identical, both data types can be compressed using the same strategies. The extension of the JPEG-2000 Part 2 containing multi-component transform is implemented only in a few specialized software packages, such as the PICTools Medical SDK for compressing volumetric medical scans (Accusoft 2014), LEADTOOLS JPEG 2000 Image Compression SDK (LEADTOOLS 2014), OpenJPEG library (OpenJPEG 2014), and Kakadu Software (Kakadu Software 2013) which, in version 7.2, was used in this study. In order to investigate the variability of the waveform cube affecting compression, additional operations were also performed prior to Kakadu compression. The flowchart of all performed operations is presented in Fig. 3 and discussed below in details.

Since the actual range of waveform sample intensities (values) varies for each band of the waveform cube and, thus, may adversely affect the decorrelating transforms, waveform cube bands were normalized before applying these transforms. In this study, three variants of the band-wise normalization were tested:

- zero-mean (ZM), where the mean value of the band was subtracted from the waveform samples for each band,
- unit-variance (UV), where beside the mean removal, sample normalization was applied so that each band had unit variance,
- no normalization, i.e. using the original cube data (OC) for comparison purposes.
- JPEG-2000 contains the full lossy compression scheme, including (1) the transform engine for data decorrelation, (2) the quantization engine for data loss/reduction, and (3) the bit encoding engine for lossless compression. Nevertheless, the influence of using data decorrelations prior to JPEG-2000 is of interest since better decorrelation usually results in a better compression rate. Therefore, as a preprocessing step, three different decorrelation methods were tested:

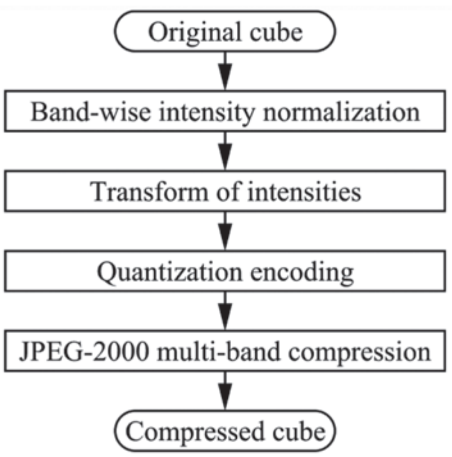



**Fig. 3:** Flowchart of operations executed during experiments.

- Karhunen-Loève transform (KLT) (Karhunen 1947, Quirk 2003),
- wavelet transform (WLT) using Cohen-Daubechies-Feauveau 5/3 wavelet (CDF 5/3) (Cohen et al. 1992),
- no transform (NOT) for comparison purposes.

KLT was applied to the cube regarded as a discrete vector stochastic process (Quirk 2003). This means that the whole waveform cube should be considered as a single large image which is the result of 'gluing' together slices of the cube along the waveform-scan line plane. Considering dimensions of the cube as $l$, $s$, and $w$ according to Fig. 1, the single large image $B$ will have the size of $w$, and $l \cdot s$ (shown on the right side in Fig. 4) and then KL-transform is calculated as:

$$C = K^T \cdot B \tag{1}$$

where:

$$K = \begin{bmatrix} k_{1,1} & k_{1,2} & \cdots & k_{1,w} \\ k_{2,1} & k_{2,2} & \cdots & k_{2,w} \\ \vdots & \vdots & \vdots & \vdots \\ k_{w,1} & k_{w,2} & \cdots & k_{w,w} \end{bmatrix}$$

is the KLT matrix whose columns are the eigenvectors of the covariance matrix of image $B$. Note that covariance of the image can be calculated two ways, depending on whether columns or rows of the image are treated as random variables. In this work, the first method was applied. $C$ is the KL-transformed single large image which is reshaped backward into the cube, and then subjected to the subsequent operations. The key of such use of KLT is the data decorrelation, resulting in packing the energy of the signal mostly in the first few bands (Quirk 2003, Vaidyanathan 1998). This could benefit the JPEG-2000 multi-band compression, where many compressed bands may contain almost no energy. KLT is reversible, which means the original image $B$ can be reconstructed based on the transformed data $C$ and the transformation matrix $K$:

$$B = K \cdot C \tag{2}$$

The inverse KLT was applied for the reconstruction (decompression) process, which includes data reshaping between waveform cube and single large image, but in the reverse order as in the compression process.

In the second test, 1D WLT was applied to each waveform separately (Fig. 4). The results of WLT are low- and high-frequency components, denoted here as *Lo* and *Hi*. Considering 1D WLT as applied in this work, both *Lo* and *Hi* components have the same length, equal to half of the length of the original signal (waveform). Note that the low-frequency component contains most of the original signal energy, thus considering such transform for all waveforms, the energy would be packed into one half of the cube bands. Similarly, the *Lo* component can be subjected to another WLT resulting in two new components having half of the length of the parent, so the original signal content will be included only in one quarter of the cube. This sequential WLT known as multi-resolution analysis (MRA) (Mallat 1989) will finally result in packing the energy of the signal in the first few bands, similar to KLT (see the length of *Lo* component in Fig. 4). The number, *n,* of possible levels of MRA depends on the length of the original signal. *n* is less than $log_2(m)$, where *m* is the length of the signal; for example, for a waveform length of 120, used in this study, the maximum MRA is 7 levels; however, only three levels were used here to avoid edge effects and length extension of the WLT components. Similarly to KLT, WLT is totally reversible.

From the perspective of compression of an 8 bit waveform cube, data normalization and transforms contradict to the idea of data re-

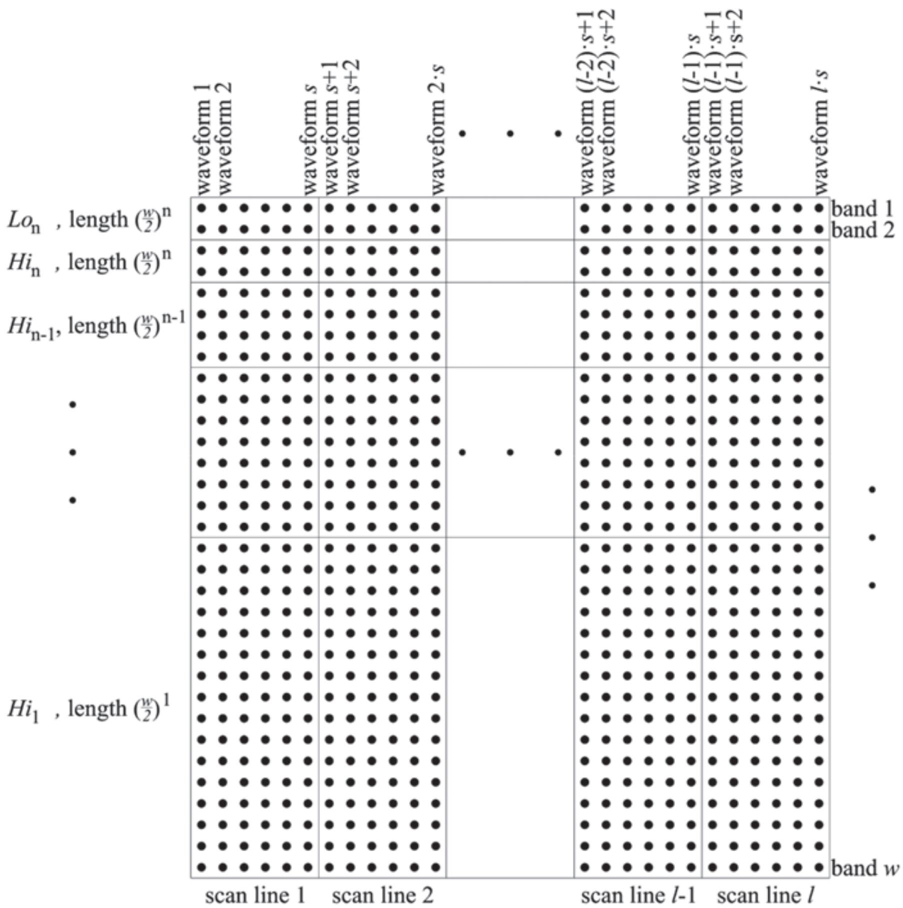



**Fig. 4:** Wavelet transform applied on the large image of the whole waveform cube.

duction since these operations result in a larger data size due to a conversion from integers into real numbers, usually in 32 bit or 64 bit representation. Additionally, some of the compressing tools do not allow floating point numbers as input pixel (sample) values. For example, the Kakadu Software accepts only 32 bit input. Therefore, the quantization encoding is needed to allow mapping floating point numbers into integers. Note that this process is invertible, known as quantization decoding, but provides no perfect reconstruction. The experiments on the test data showed that an 8 bit range would be too short to avoid large quantization errors, and, thus, more bits for the quantization base are needed. In this experiment, a linear quantizer with a 28 bit base length was used providing much larger dynamic range than that of the original data (8 bits). The amount of the introduced quantization noise and other data distortion, such as numerical errors of data normalization and transforms not caused by JPEG-2000 compression, was empirically evaluated. First, the test waveform cubes were subjected to forward processing, including data normalization, transform, and quantization encoding; and then, the inverse operation, i.e. quantization decoding, inverse transform, and reverse data normalization, was carried out. The observed maximal absolute difference between the value of the original and reconstructed waveform sample was on the level of 1e-4 that equals to 0 in integer terms.

The results of the investigation of image based waveform cube compression (Jóźków et al. 2015) showed that the best compression performance was obtained for the set of images where the single image was formed by all waveforms of a single scan line (according to $s$ and $w$ dimensions in Fig. 1). Therefore, the waveform cube was rotated prior to multiband compression in the Kakadu Software, thus the dimension $l$ of the cube was treated as the band during JPEG-2000 multi-component transform.

In the case of lossy compression, the user can decide partially about the amount of data degradation and compression ratio. Depending on the implementation, a quality factor is used to control the desired compression ratio. In the Kakadu Software, this user input parameter is the bits per pixel ratio, i.e. the average number of bits for a single pixel in the compressed file. Obviously, this value must be smaller than the bit depth in the original image in order to gain a reduction in the file size, but a smaller ratio means a larger data distortion due to compression. The resulting ratio might be slightly different from the value given by the user because the compression strength depends also on the inherent parameters of the data. Since the original waveform data is 8 bits, experiments were executed for 20 parameters, ranging from 0.4 to 8 bits with a step size of 0.4 bits. Note that Kakadu compressed JPEG-2000 file might include several reconstruction qualities, in other words, one file may contain data compressed with different ratios at the same time, but this option was not tested during this investigation.

## 4 Performance of Waveform Data Compression

Compression performance might be evaluated from different perspectives, such as the achieved compression ratio and reconstruction error. The compression ratio is defined by the percentage of the compressed file size with respect to the original one. In the case of image compression, the bits per pixel ratio (BPP) or the bits per pixel per band ratio (BPPPB) are frequently used to describe the compression ratio, depending whether a single- or a multi-band image is compressed. The BPP value is the number of bits used to store a single pixel in the compressed image. Due to the similarity of multi-band images and waveform cubes, the BPPPB was used in this study. Note that a pixel of the image cube is equivalent to a waveform sample in the waveform cube. Knowing the BPPPB ratio for the original and compressed cubes, the compression ratio or percentage ratio can be easily calculated. The compression ratio is also affected by the file header, or metadata, essential for decompression. This data is kept in the compressed file, increasing its size. The final BPPPB ratio was calculated on the basis of the file size produced by the Kakadu Software and the number of waveform samples in the waveform cube. Note that the size of other data, mandatory for reconstruction, such as mean values of bands in the case of ZM data or $K$ matrix in the case of KLT transform and quantization parameters, were not included in this calculation. The omission of these parameters in the size calculations does not change the BPPPB ratio significantly, because the size of these parameters is much smaller than the size of the compressed cube.

The performance of lossy compression methods is related to the data degradation, the distortion (noise) introduced due to quantization included in the compression process. Reconstruction noise (error) can be measured by different parameters, such as signal to noise ratio (SNR), peak signal to noise ratio (PSNR) (Vaidyanathan 1993), or just by giving simple statistics of the differences between reconstructed and original data. In this work data distortion was measured by the SNR, which is based on the variance of waveform samples and their differences:

$$SNR = 10 \cdot \log_{10} \frac{\sigma_o^2}{\sigma_{o-r}^2} \quad (3)$$

where

$\sigma_o^2$ – variance of all the original waveform samples,

$\sigma_{o-r}^2$ – variance of waveform sample differences between original and compressed data.

For a low data degradation, the SNR is large, and it approaches infinity for a perfect reconstruction. Note that the calculated SNR describes only quantization noise of the original waveform signal.

Another aspect of compression performance is the computational cost, the compression and decompression speed and use of computer resources. In our previous work (Jóźków et al. 2015), it was concluded that 2D JPEG-2000 based compression is fast enough to support waveform compression during the acquisition process in the sensor system, as waveforms forming single scan lines might be compressed progressively. Similarly, waveform cubes might be compressed progressively by the approach presented in this work. However, the additional transforms for data decorrelation introduced in this experiment, e.g. KLT, make the algorithm much more complex and, consequently, resulting in a much slower execution than the 2D compression. Obviously, any computation on larger datasets like waveform cubes requires much more memory resources than computation performed on a small part of this data like the single image slice. These issues were not considered in this work in evaluating the computational expenses of the compression performance.

Finally, the impact of compression noise can be evaluated looking at the results of subsequent waveform data post processing tasks, but executed on the decompressed data. For example, the Gaussian waveform decomposition should result in the same number of detected echoes with insignificantly different parameters from those obtained in processing the original uncompressed FWD. Note that even well-established waveform decomposition methods produce varying results, just as the number of parameters used to describe the components can be different, for example, 3 and 4 (Chauve et al. 2007), or even 5 (Laky et al. 2010). Based on the earlier investigation (Jóźków et al. 2015), it was concluded that the SNR of above 30 dB – 35 dB in typical airborne LiDAR data assures an acceptable waveform reconstruction error which will not cause significant changes in waveform shape and, consequently, does not affect the results of subsequent FWD processing, in particular waveform decomposition.

## 5 Results and Discussion

Numerical experiments were performed with all combinations of the three decorrelation techniques (OC, ZM, UV) and three transforms (NOT, KLT, WLT) at 20 different user specified compression ratios for two test waveform cubes C1 and C2. To discuss and analyze the effects, experimental results are visualized by showing the SNR as a function of the obtained BPPPB in Fig. 5. For comparison purposes, results obtained for the same data but using the earlier proposed approach, based on JPEG-2000 compression of waveforms arranged in the set of 2D images (Jóźków et al. 2015) was added to the figures. It should be also explained why 2D compression did not result in large SNR or BPPPB ra-

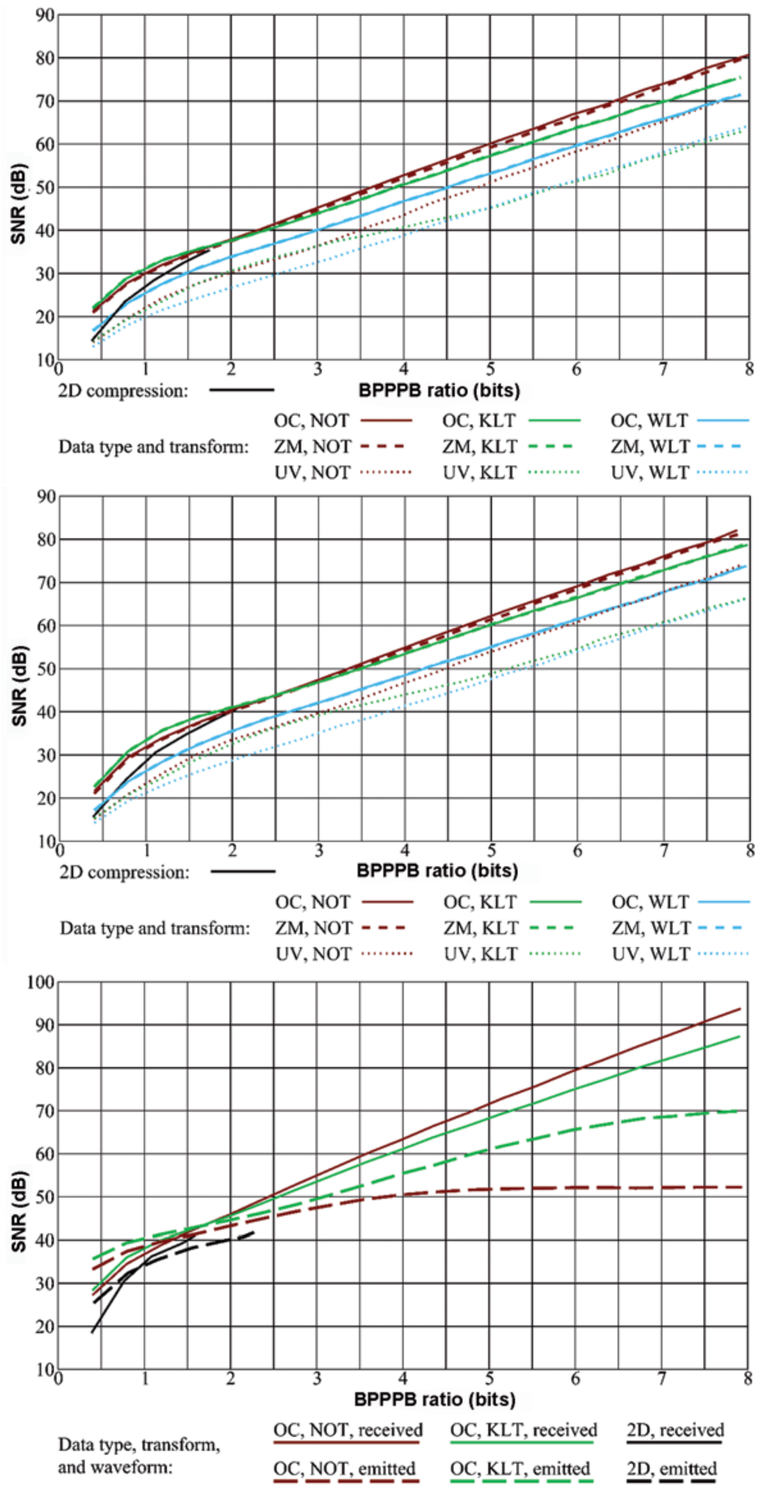



**Fig. 5:** SNR as a function of BPPPB ratio, BPPPB = bits per pixel per band ratio.

tio. For the user input ratios 2.4 bits and larger, the obtained SNR was always similar, about 35 dB and 41 dB for C1 and C2, respectively, as well as similar was the BPPPB ratio, about 1.7 and 2 bits for C1 and C2, respectively. This explains the higher dynamic of JPEG-2000 based 3D compression than 2D compression of the waveform cube.

Comparing results obtained for C1 and C2 test cubes, it is clearly seen that the impact of using different sensors for collecting FWD for the same area is insignificant; a slightly larger (maximally 5 dB) SNR was obtained for the test cube C2. The most likely reason is the lower internal complexity of cube C2, as the compression of images containing less details results in lower reconstruction noise for the same compression rate. Among the used transforms, the worst SNR was obtained for WLT. This could be explained with the fact that *Lo* and *Hi* components are usually in very different ranges and, thus, a non-linear quantizer might be more appropriate for preserving better dynamic range of the quantized component values prior to JPEG-2000 compression. Differences between the other two transforms, KLT and NOT, are maximally of about 5 dB for the same BPPPB ratio, where higher SNR was obtained for KLT in the case of small ratios and NOT in the case of large ratios. Considering that the used KLT is adaptive (needs to be calculated for every dataset), and therefore highly computational expensive, and the improvement of the SNR by a few dB only for small BPPPB ratios compared to the case of using no transform (NOT), it is clearly not beneficial in practice. Obviously, a fixed KLT matrix for similar datasets might be used to reduce the number of computations, but it is extremely difficult to find representative datasets of FWD to create a fixed KLT base (Jóźków et al. 2015). The last aspect of the investigated approach is the data normalization method. The worst SNR was obtained for UV. Differences between OC and ZM are insignificant, which implies that data do not require any normalization and the intensities of the original waveform samples are suitable for the compression.

Based on the C1 and C2 results, compression experiments with the C3 dataset were executed only for the best performing data normalization (OC) and transforms (NOT, KLT), resulting in similar performance for compressing received waveforms. SNR obtained for C3, however, was about 10 dB larger than for the C1 and C2 cubes. This may be explained by the simpler object complexity of the C3 area. Similarly, a difference of performance between compressing cubes of emitted and received waveforms was observed, as a large number of zero samples in the received cube resulted in higher SNR for large compression ratios. In contrast, the strong similarity of the emitted waveforms allowed for higher SNR for small compression ratios. This close similarity of the outgoing waveforms was also exploited by applying an additional decorrelating transform. For example, KLT applied to the emitted cube resulted in higher SNR, especially for large compression ratios, than in the case where the preprocessing transform was not applied (NOT). Since the outgoing waveforms change very little, instead of using adaptive KLT, a fixed KLT may be applied to reduce the computational expenses. Finally, comparing results of 2D with 3D compression approaches, the same observations can be noted as for the smaller cubes C1 and C2. Compression performance differences for emitted and received cubes in the 2D approach follow the same pattern as for 3D approach.

Comparing waveform compression results of the earlier 2D and here proposed 3D methods, both based on the JPEG-2000 Standard, the difference is not significant; for example, for unnormalized and untransformed data, the 3D approach for small BPPPB ratio gives a slightly larger SNR than the 2D approach, the difference being about 5 dB – 10 dB. Clearly, the flexibility of the 3D approach to adjust the data degradation and compression ratio is an obvious advantage.

## 6 Conclusions

This work investigated the feasibility of compressing waveform cube using multi-component JPEG-2000 extension. The tested approaches included additional computations, such as data normalization and transforms prior to JPEG-2000 compression.

Based on the numerical experiments performed on three waveform cubes, it was concluded that in relation to 2D JPEG-2000 based compression, the multi-component extension is more flexible, because the user can chose between a larger range of compression ratios and select larger file sizes to obtain very low data loss, which was not possible for the 2D approach. For larger compression ratios (small BPPPB ratio), however, both 2D and 3D approaches result in similar performance in terms of data degradation and reduction of the file size. Note that for both approaches, this similar performance was obtained for the same cube orientation where bands (images) were formed from waveforms representing single scan lines, offering more flexibility for the practical use where the same compression tool might be used with two different variants depending on the available computational power. More importantly, both single images and waveform cubes can be then progressively compressed according to the waveform data acquisition order. The advantage of 2D approach is speed, but the disadvantage is the low dynamic range and the inability to achieve a large SNR. Multi-component compression is slower, but gives the user more choices on deciding about the amount of data degradation.

The used implementation of the JPEG-2000 Standard with wavelet-based multi-component transform performed well in decorrelating the original waveform cube data. Additional data normalization or transform of the original waveform cube did not show significant improvements in 3D compression performance, and only caused extra computational costs.

Finally, one more advantage of using JPEG-2000 Standard for compressing waveforms in both approaches is the possibility of keeping different reconstruction levels in one, but larger file. It can be useful for data distribution with different distortion and compression levels depending on the application requirements.

## References

Accusoft, 2014: PICTools Medical SDK. – http://www.accusoft.com/picmedx.htm (31.10.2014).

ASPRS, 2013: LAS specification, version 1.4 – R13. – http://www.asprs.org/a/society/committees/standards/LAS_1_4_r13.pdf (12.6.2014).

Biasizzo, A. & Novak, F., 2013: Hardware Accelerated Compression of LIDAR Data Using FPGA Devices. – Sensors **13** (5): 6405–6422.

Bunting, P., Armston, J., Lucas, R.M. & Clewley, D., 2013: Sorted Pulse Data (SPD) Library. Part I: A generic file format for LiDAR data from pulsed laser systems in terrestrial environments. – Computers & Geosciences **56:** 197–206.

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): 102–107.

Cohen, A., Daubechies, I. & Feauveau, J.-C., 1992: Biorthogonal bases of compactly supported wavelets. – Communications on Pure and Applied Mathematics **45** (5): 485–560.

GeMMA Lab, 2009: LASCompression. – http://gemma.uni-mb.si/lascompression (12.6.2014).

Hug, C., Ullrich, A. & Grimm, A., 2004: Litemapper-5600-a waveform-digitizing LiDAR terrain and vegetation mapping system. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **36** (Part 8/W2): 24–29.

Heinzel, J. & Koch, B., 2011: Exploring full-waveform LiDAR parameters for tree species classification. – International Journal of Applied Earth Observation and Geoinformation **13** (1): 152–160.

Isenburg, M., 2011: LASzip: lossless compression of LiDAR data. – http://www.cs.unc.edu/~isenburg/lastools/download/laszip.pdf (12.6.2014).

Isenburg, M., 2014: PulseWaves. – https://github.com/PulseWaves (12.6.2014).

Jóźków, G., Toth, C., Quirk, M. & Grejner-Brzezinska, D., 2015: Compression Strategies for LiDAR Waveform Cube. – ISPRS Journal of Photogrammetry and Remote Sensing, **99** (1): 1–13.

Kakadu Software, 2013: Kakadu Software – Home. – http://www.kakadusoftware.com (12.6.2014).

Karhunen, K., 1947: Über lineare Methoden in der Wahrscheinlichkeitsrechnung. – Annales Academiae scientiarum Fennicae: Mathematica – Physica **37:** 1–79, Universität Helsinki, Finnland.

Kulkarni, P., Bilgin, A., Marcellin, M.W., Dagher, J.C., Kasner, J.H., Flohr, T.J. & Rountree, J.C., 2006: Compression of earth science data with JPEG2000. – Motta, G., Rizzo, F. &

Storer, J.A. (eds.): Hyperspectral Data Compression. – Springer: 347–378.

Koranne, S., 2011: Hierarchical data format 5: HDF5. – Handbook of Open Source Tools: 191–200, Springer.

Laky, S., Zaletnyik, P. & Toth, C., 2010: Land classification of wavelet-compressed full-waveform LiDAR data. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **38** (Part 3A): 115–119.

LEADTOOLS, 2014: LEADTOOLS JPEG 2000 Image Compression SDK. – https://www.leadtools.com/sdk/compression/jpeg2000.htm (31.10.2014).

Lizardtech, 2014: LiDAR Compressor. – http://www.lizardtech.com/products/lidar (6.12.2014).

Mallat, S.G., 1989: A theory for multiresolution signal decomposition: the wavelet representation. – IEEE Transactions on Pattern Analysis, and Machine Intelligence **11** (7): 674–693.

Mallet, C. & Bretar, F., 2009: Full-waveform topographic lidar: State-of-the-art. – ISPRS Journal of Photogrammetry and Remote Sensing **64** (1): 1–16.

Mallet, C., Bretar, F., Roux, M., Soergel, U. & Heipke, C., 2011: Relevance assessment of full-waveform lidar data for urban area classification. – ISPRS Journal of Photogrammetry and Remote Sensing **66** (6): 71–84.

Mongus, D. & Žalik, B., 2011: Efficient method for lossless LIDAR data compression. – International Journal of Remote Sensing **32** (9): 2507–2518.

OpenJPEG, 2014: OpenJPEG library: an open source JPEG 2000 codec. – http://www.openjpeg.org/ (31.10.2014).

Parrish, C.E. & Nowak, R.D., 2009: Improved Approach to LIDAR Airport Obstruction Surveying Using Full-Waveform Data. – Journal of Surveying Engineering **135** (2): 72–82.

Pirotti, F., 2011: Analysis of full-waveform LiDAR data for forestry applications: a review of investigations and methods. – iForest-Biogeosciences and Forestry **4** (3): 100–106.

Pradhan, B., Kumar, S., Mansor, S., Ramli, A.R. & Sharif, A.R.B.M., 2005: Light detection and ranging (LIDAR) data compression. – KMITL Science and Technology Journal **5** (3): 515–523.

Quirk, M.D., 2003: Theory of Principal Component Filter Banks with Applications to Multicomponent Imagery. – Ph.D. thesis, The University of Texas at Austin, Austin, TX, USA.

Reitberger, J., Krzystek, P. & Stilla, U., 2008: Analysis of full waveform LIDAR data for the classification of deciduous and coniferous trees. – International Journal of Remote Sensing **29** (5):1407–1431.

SPDLib, 2013: The SPDLib Documentation Wiki. – http://www.spdlib.org/ (30.10.2014).

Stilla, U. & Jutzi, B., 2008: Waveform analysis for small-footprint pulsed laser systems. – Shan, J. & Toth, C.K. (eds.): Topographic laser ranging and scanning: Principles and processing: 215–234, CRC Press.

Taubman, D. & Marcellin, M., 2002: JPEG2000: Image Compression Fundamentals, Standards and Practice. – Springer.

The HDF Group, 2014: HDF Group – HDF5. – http://www.hdfgroup.org/HDF5/ (30.10.2014).

The Internet Engineering Task Force (IETF), 1996: RFC 1951 – DEFLATE Compressed Data Format Specification Version 1.3. – http://tools.ietf.org/html/rfc1951 (30.10.2014).

Toth, C., Laky, S., Zaletnyik, P. & Grejner-Brzezinska, D., 2010: Compressing and classifying LiDAR waveform data. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **38** (Part 1): (on CD-ROM).

Vaidyanathan, P.P., 1993: Multirate Systems and Filter Banks. – Prentice Hall PTR.

Vaidyanathan, P.P., 1998: Theory of Optimal Orthonormal Subband Coders. – IEEE Transactions on Signal Processing **46** (6): 1528–1545.

Address of the Authors:

Grzegorz Jóźków, Charles Toth & Dorota Grejner-Brzezinska, Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Hitchcock Hall, 2070 Neil Avenue, US-43210 Columbus, OH, USA, Tel.: +1-614-292-7681, +1-614-292-8787, e-mail: {jozkow.1} {toth.2} {grejner-brzezinska.1}@osu.edu

Mihaela Quirk, The National Intelligence University, e-mail: mihaela.quirk@dodiis.mil

Manuskript eingereicht: August 2014
Angenommen: Februar 2015