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GEOBIA methods for LiDAR obtained point clouds

SUMMARY: *This paper critically analyses the state of the art provided in today's scientific »market of knowledge« concerning the subject of object delineation from LiDAR obtained 3D point clouds. Such approach became a very popular subject in many scientific fields (forestry, geography, archaeology, etc.). The author will give multiple examples on how other authors deal with object extraction and delineation from 3D point clouds. He will also give a brief introduction and explanation of terms such as GEOBIA and LiDAR with a short reference to multiple return and full waveform LiDAR data. Pros and cons of existing approaches will be discussed along with conclusions based on what has been reported so far in scientific literature.*

KEYWORDS: *GEOBIA, OBIA, point cloud, LiDAR, fullwaveform LiDAR data*

1. INTRODUCTION

»Time is money.« Benjamin Franklin

Today we are faced with an ever growing need of producing fast and reliable geospatial products. In the past few years geospatial information became openly public in such a way that even a regular user nowadays, is familiar with terms like GPS, AGPS, location, longitude, latitude, positional accuracy, navigation, 3D space, etc.

More and more devices that we use in our daily life have some kind of spatial sensor built into. Some even allowthe user to obtain data on their own by recording their position or programming simple applications which can be used on a smartphone or similar device with built-in location sensors to obtain position. In a more professional surrounding, it has become more important to have as realistic representation of space as possible with minimum time and money investment. In one of such efforts to simplify the process of gathering data, LiDAR system was introduced. It allowed the user to collect a vast amount of data in a matter of minutes and cut back on the time needed to survey a certain area. The main advantage of the technique is that it provides a direct method for 3D data collection and is highly accurate because of the millimetre and centimetre level laser raging accuracy and precise sensor platform orientation supported by an integrated position and orientation system (Shan and Toth, 2008). The problem which emerged from the usage of this type of fast system is how to model such a vast amount of data without too much labour power in the process. Figure 1.1 shows a graphical overview of different steps in terrestrial laser scanning process and their grade of automation (same can be projected to airborne laser scanning process).

Once we obtain 3D point cloud from our LiDAR system we need to process it. 3D point cloud processing can be divided into two different categories. Deliverables can be extracted straight from the point cloud without further processing, or by firstly creating a 3D surface model from the point cloud and extracting the deliverables from the surface model. Over the past years it has been noticed that more and more scientists try to implement object based image analysis (OBIA) into automatization process of object extraction from 3D point clouds. There are many approaches which try to delineate objects from 3D point clouds by using OBIA methodology (Wang and Schenk, 2000; Rottensteiner and Jansa, 2002; Alharthy and Bethel, 2002; Miliaresis and Kokkas, 2007; Sohn and Dowman, 2007; Vu et al., 2009; Rottensteiner and Briese, 2001; Wang, 1998; Vosselman and Dijkman, 2001; Brenner, 2005; Haala and Brenner, 1999; Hofmann et al., 2002; Matikainen et al., 2003; Weinacker et al., 2004; Hu et al., 2004) and some of them are either fully automated or semi automated. The main problem is the lack of a general, instead of object specific approach, but this will be discussed latter on in the article.

2. (GE)OBIA AND LIDAR/FULLWAVEFORM LIDAR

»A leader is someone who steps back from the entire system and tries to build a more collaborative, more innovative system that will work over the long term.« Robert Reich

Object based image analysis or OBIA has given a completely new approach to analysis of remote sensing data. The user nowadays is no more confronted with single pixel of a low spatial resolution but with a lot of pixels of very high spatial resolution. Blaschke and Strobl (2001) raised a provocative question: »what's wrong with pixels?«, are the methods used in the 70s still good for modern imagery data? They argued for classification of homogeneous groups of pixels which would then reflect objects of interest in reality and the usage of algorithms to delineate objects based on contextual information given in an image on the basis of texture or fractal dimension. OBIA builds its foundations on older segmentation, edge-detection, feature extraction and classification concepts that have been around through the past decades. OBIA gives a new approach to analysis of remotely sensed imagery. Extracted objects contain additional spectral information when compared to single pixels (mean values per band, median values, minimum and maximum values, mean ratios, etc.) and even spatial dimensions (distance, neighbourhood, topologies, etc.) are more valuable because they provide a more realistic comparison when used on objects rather than pixels. Lately, discussion has been risen about geographic space which is to be included in the name and if OBIA should be GEOBIA or Geographic Object Based Image Analysis. The name OBIA may be too broad because it is used for the whole variety of disciplines (medicine, computer vision, material sciences), but with the added prefix it would be clearly stated that it is a part of GIScience (Blaschke, 2010).

Airborne LiDAR systems, on the other hand, have provided a perfect method to obtain large amount of data quickly. They can generate very accurate data at high spatial resolution. If combined with some other data acquired from other remote sensing systems (multispectral, hyperspectral, etc.), obtained data can then be introduced to new exciting possibilities for 3D analysis and visualisation. Both airborne and terrestrial LiDAR systems have become major scientific tools in a wide range of subjects such as Archaeology, Agriculture, Botany, Biology, Earth Science, Ecology, Forestry, Geography, Environmental Science and Landscape Ecology, etc. Aerial LiDAR surveys have a typical resolution from about 10 points per square meter (fixed-wing aircraft) to 200 points per square meter (helicopters), ground based systems produce considerably higher measurement densities. Once the data is collected additional processing is necessary to generate point cloud which can then be used for further analysis as shown in figure 2.1.

LiDAR can record different kinds of returns from terrain. They could either be primary or secondary. Primary returns originate from the first objects a LiDAR pulse encounters, often upper surface of a vegetation canopy (figure 2.2). Secondary returns originate from portion of a pulse which passes through gaps in the canopy into the interior structure of leaves and branches to lower vegetation layers and the ground surface and creates echoes (figure 2.2).

Over the past few years it has become popular to use full waveform data for data analysis. New technology of full-waveform airborne laser scanning systems permits digitalization of the complete waveform of each backscattered pulse. It gives more control to an end user in the interpretation process of physical measurement and provides additional information about the structure and the physical backscattering characteristics of the illuminated surfaces. There are two conceivable approaches for processing the vertical profiles recorded by the new generation of airborne full waveform LiDAR sensors (Mallet and Bretar, 2009). The first one consists of decomposing the waveform into a sum of components of echoes and characterizing different targets along the path of the laser beam. The second preserves the whole 1D signal. The first approach aims to maximize the detection rate of relevant peaks to generate a denser point cloud; it can help to characterize different targets along the path of laser beam and it is interesting for usage in the area of forestry application. Spatio-temporal analysis is used in the second approach to find features within a 3D waveform space and it is suitable for urban areas where geometry is regular. The extracted points on different tree species from full-waveform data post-processing are shown in figure 2.3. The obtained point clouds are denser than those obtained only with the first/last plus method. The usage of the above mentioned methods in scientific research will be discussed further on in the article.

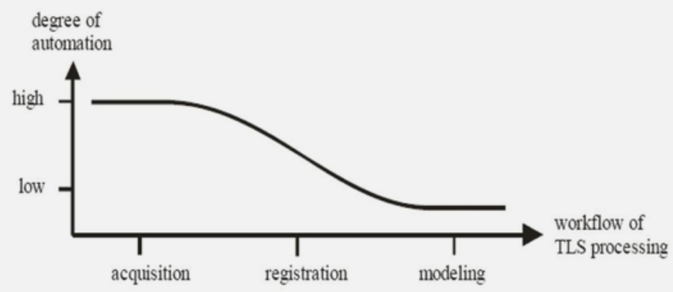

Figure 1.1. Automation workflow for terrestrial laser processing (A. Gruen, 2009)

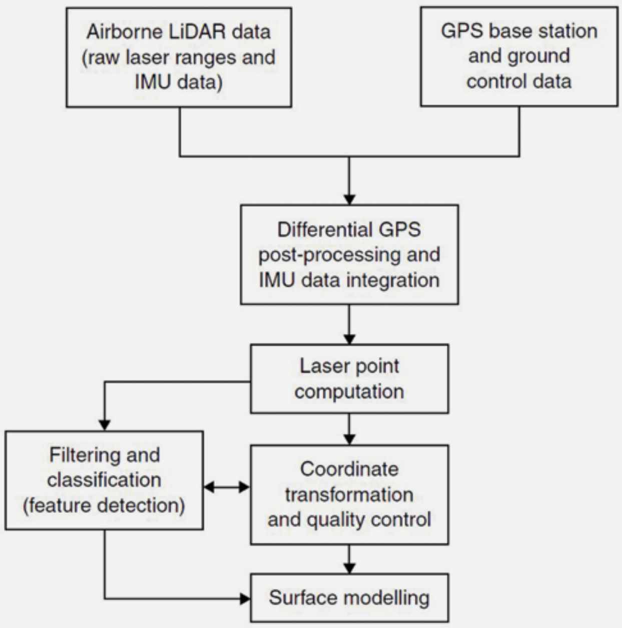

Figure 2.1. Schematic overview of main data processingstages to integrate and convert airborne sensor and associated ground based recordings into point cloud and derived data products (Heritage and Large, 2009)

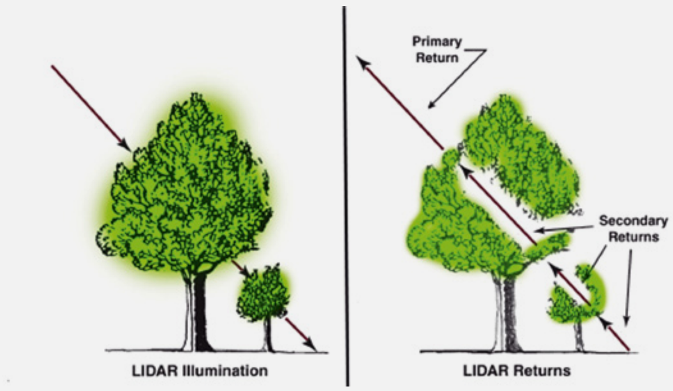

Figure 2.2. Primary and secondary lidar returns

3. DEVELOPEMENT OF OBJECT EXTRACTION APPROACHES

»The book is there for inspiration and as a foundation, the fundamentals on which to build.« Thomas Keller

(GE)OBIA has given a new approach when it comes to dealing with remote sensing imagery while LiDAR has provided a fast and reliable source of spatial information in form of 3D point clouds. Many scientists tried to combine both methods in order to come up with a set of new methods and algorithms which would allow them to extract objects straight from the 3D space in a fast and efficient way (Wang and Schenk, 2000; Rottensteiner and Jansa, 2002; Alharthy

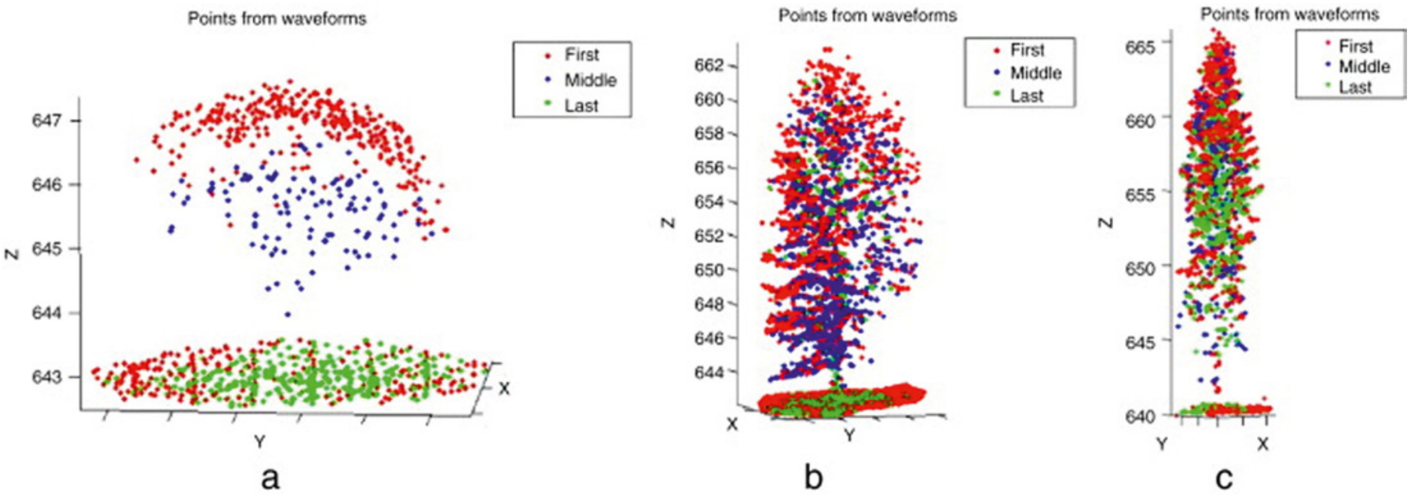

Figure 2.3. Extracted points on different tree species from full-waveform data post-processing. (a)Deciduous (leaf-on). (b)Deciduous (leaf-off). (c)Coniferous. Red, green and blue points correspond respectively to the first, last and intermediate extracted pulses (Mallet and Bretar, 2009).

and Bethel, 2002; Miliaresis and Kokkas, 2007; Sohn and Dowman, 2007; Vu et al., 2009; Rottensteiner and Briese, 2001; Wang, 1998; Vosselman and Dijkman, 2001; Brenner, 2005; Haala and Brenner, 1999; Hofmann et al., 2002; Matikainen et al., 2003; Weinacker et al., 2004; Hu et al., 2004). All of the approaches are object specific (building extraction, tree crown delineation, road extraction, ect.) and are in their nature either automated of semi-automated.

When we talk about approaches that use (GE)OBIA/LiDAR combination for forestry application we can point out Weinacker et al. (2004) who tried to develop filtering, segmentation and modelling modulesfor LiDAR and multispectral data for an automatic forest inventory system. They started with raw laser data as input and ended up with derived tree parameters for each tree. Process included DTM/DSM filtering based on active contour theory. The filtering algorithm starts with the creation of a raster area, using pixel sizes in relation to density of the given raw data points. Based on these constructed raster surfaces DTM/DSM filtering is done. The next step was tree tops detection from smoothed DSM by means of local maximum filtering. Starting from the local maxima, a pouring algorithm is detecting the approximate tree border. The last step included tree species classification and modelling based on two different approaches: statistical, based on linear stepwise discriminant analysis and the second one based on the form fitting algorithm, where an extended super quadric (ESQ) is used to fit trees either based on raw laser data or based on the DSM. The approach can be used as a fundament for a semi-automatic inventory system based both on LiDAR and multi-spectral data. Livny et at., (2010) tried to recreate realistic tree models from the point cloud. Their approach robustly reconstructed skeletal structures of trees, from which full geometry could be generated. Their optimization aims to reconstruct major skeletal branches of the captured trees, resulted in a graph structure called the Branch-Structured Graph or BSG for each tree. Each tree represented by BSG is defined as a spatially embedded and connected directed acyclic graph. The root node of the BSG corresponds to the base of the tree. BSG nodes are connected by straight edges and lie spatially in the centre of tree branches. The branch is simple if it contains no branching points and is represented by a Branch-Chain (BC) which is a sub-graph of the BSG given by a chain of connected nodes and edges. The whole reconstruction pipeline for extracting BSGs consists of three steps, the first two are iterated. The first step initializes BSG from the points (detection of ground surface, three root extraction. Dijkstra's algorithm is used to extract disjoint initial BSGs). The second step refines the BGS graph by assigning an importance weight to each vertex based on the sizes of the sub-trees (for each BSG, a smooth orientation field is generated by minimizing the sum of directional differences between adjacent edges, weighted by these importance values. The orientation field is used to optimize spatial embedding of the BSGs. This is done to achievethe balance between tree smoothness and centred fitting to the point samples.) The third step consists of inflating BSGs into the tree geometry (they compute the thickness or skeleton radius values along the edges of the BSGs guided by the above optimization criteria.). The sample of tree skeleton built from such approach is given in figure 2.4.

Reitberger et al. (2008) analysed full waveform LiDAR data. They used it to do the classification of deciduous and coniferous trees. They described methodology for tree species classification by using features that were derived from small-footprint full LIDAR data. 3-dimensional coordinates of the laser beam reflections, the intensity, and the pulse width were extracted by a waveform decomposition, which fits a series of Gaussian pulses to the waveform. Multiple reflections were detected, and even overlapping pulse reflections were distinguished, a much higher point density was achieved compared to the conventional first/last-pulse technique. The tree crowns were delineated from the canopy height model (CHM) using the watershed algorithm. The CHM posts are equally spaced and robustly interpolated from the highest reflections in the canopy. Tree features computed from the 3-dimensional coordinates of the reflections, the intensity and the pulse width were used to detect coniferous and deciduous trees by an unsupervised classification. The methodology was applied to datasets that have been captured in the leaf-on and leaf-off conditions for Norway spruces, European beeches and Sycamore maples. The classification lead to an overall accuracy of 85% in a leaf-on situation and 96% in a leaf-off situation.

When it comes to building extraction we can also find a plethora of different approaches. Vu et al. (2009) proposed a multi-scale solution for building extraction from LiDAR and image data. The approach is based on mathematical morphology using nonlinear scale-space employing area morphology to extract building features from remotely sensed elevation and spectral data. They extracted complex structures as multi-part objects in which each part is represented on a scale depending on its size. Final building footprints are represented by the boundary of the largest part. The obtained spectral data, as in the previous mentioned case, are used to remove vegetation and possibly classify the building roof materials. Authors classify the approach a fully automated which can make use of both spectral and elevation data working well with any nDSM and spectral data source. Nan et al. (2010) introduced an interactive tool which enables a user to quickly assemble an architectural model directly over a 3D point cloud acquired from large-scale scanning of an urban scene. The user loosely defines and manipulates simple building blockscalled SmartBoxes over

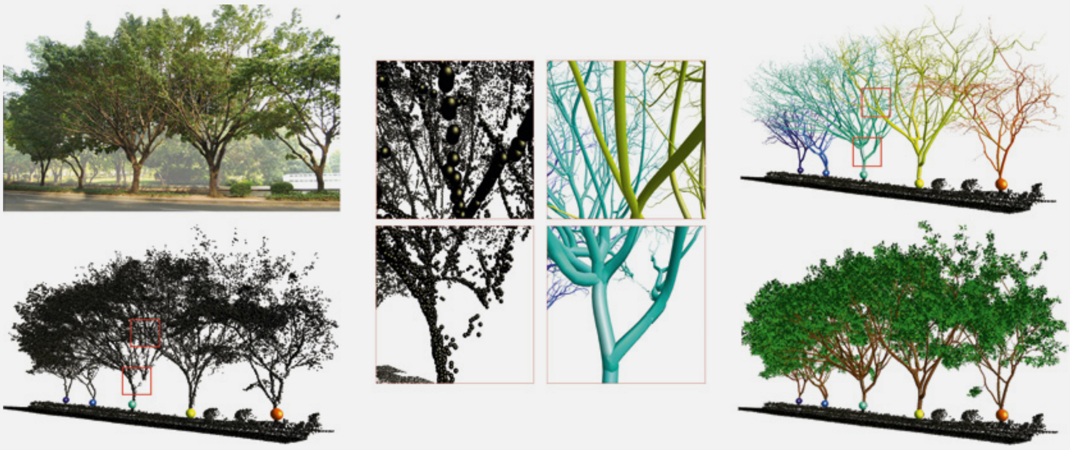

Figure 2.4. A scene of five trees automatically reconstructed by skelet growing algorithm. The images show a photo of the scene, point cloud, reconstructed trees, and textured models with leaves. The insets show the ability of method to handle overlapping crowns and missing data (Livny et at., 2010)

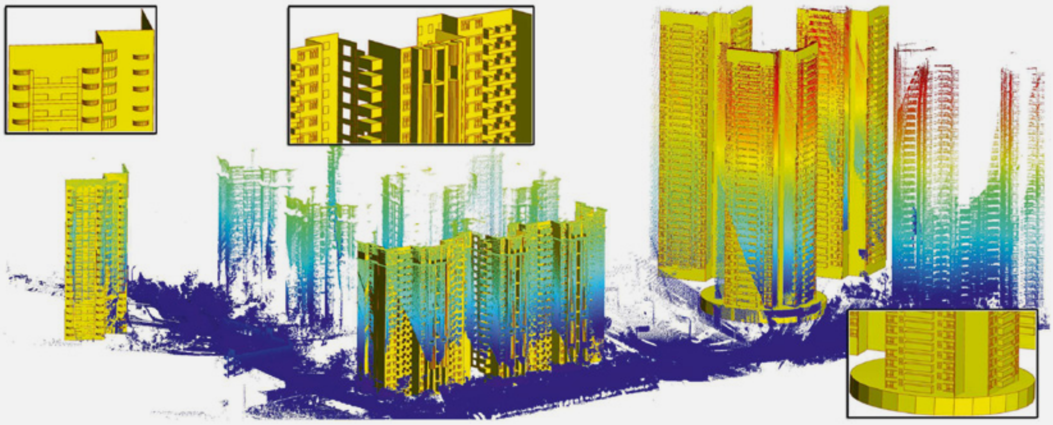

Figure 2.5. A large-scale urban architectural scene is reconstructed in details from a noisy and sparse LiDAR scan using SmartBoxes interactively. Close-up views show the reconstructed details of 3D architectural structures (Nan et al. 2010)

the point samples. These boxes quickly snapto their proper locations to conform to common architectural structures. The key idea is that the building blocks are smart in the sense that their locations and sizes are automatically adjusted on-the-fly to fit well to the point data, while at the same time respecting contextual relations with similar nearby blocks. SmartBoxes are assembled through a discrete optimization to balance between two snapping forces defined respectively by a data-fitting term and a contextual term, which together assist the user in reconstructing the architectural model from a sparse and noisy point cloud. They show that a combination of the user's interactive guidance and high-level knowledge about the semantics of the underlying model, together with the snapping forces, allows the reconstruction of structures which are partially or even completely missing from the input. Figure 2.5 shows implementation of SmartBoxes approach. Miliaresis and Kokkas (2007) used LiDAR generated DEM and geomophometric region growing segmentation combined with median filtering to identify seed cells. Labelling components are connected: size filtering and object labelling, object parametric representationon the basis of slope and elevation attributes and classification. All of these elements are used to delineate building class within the study area. This approach is not fully automated and it requires a certain level of users' interaction for some crucial parameters which differ based on situation.

Alharthy and Bethel (2002) developed a fast low cost algorithm. It is used for extraction of 3D features in urban areas from LiDAR data only. It consists of a two steps approach, usage of »first minus last« return analysis and utilizationof the local statistical interpretation. »First minus last« method is used to determine if the object is a tree or a solid construction based on calculated height. Local statistical analysis method is used to determine surface smoothness from a root mean square error calculated for each window square and used as an attribute. If the RMSE is high then it indicates an irregular surface that can be interpreted as a tree or a rough surface. Since building roofs are smooth surfaces this method was used to remove noise and some non-building objects. DEM was extracted from filtered data and the above ground objects were obtained by subtracting DEM from filtered DSM. These non-terrain objects were threshold to remove the remaining non-penetrable objects like cars etc. In the final step primitive raster objects were used to derive vector footprint delineation and some geometric constraints which were then able to create the building polygons.

There are also algorithms concentrated on automated road extraction; Hu et al. (2004) tried to develop automatic road extraction from dense urban area by integrating processing of high resolution imagery and LiDAR data. Their method firstly detects the primitives or clues of the roads and the contextual targets both from the colour image and LiDAR data by segmentation and image analysis. Intensity and height data are used and segmented to create road areas and open areas. »Iterative Hough transform« and »Morphologic operation« are used to generate candidate objects. From optical imagery by means of pixel based classification grass land, tree areas and vehicles are detected and this data is used along with generated candidate road and parking stripes to produce verified road and parking stripes. Both of them went through topology detection and final road network was detected.Another method for the automatic detection of roads from airborne laser scanner data was presented by Clode et al. (2004). Traditionally, intensity information has not been used in feature extraction from LIDAR data because the data is too noisy. They dealt with using as much of the recorded laser information as possible thus both height and intensity were used. To extract roads from a LIDAR point cloud, they used hierarchical classification technique to classify the LIDAR points progressively into road or non-road. An accurate digital terrain model (DTM) was created by using successive morphological openings with different structural element sizes. Individual laser points were checked for both a valid intensity range and height difference from the subsequent DTM. A series of filters were passed over the road candidate image to improve the accuracy of the classification. The success rate of road detection and the level of detail of the resulting road image both depend on the resolution of the laser scanner data and the types of roads expected to be found.

All of the above mentioned approaches have their own strengths when it comes to usage for an object specific case. They are able to produce specific objects from a point cloud. Most of them are still semi-automatic even though there are some cases of fully-automated approach. None of them are directly transferable on other object types. Building extraction methodology is only good for buildings; it is of no use to try to use the same approach on forestry application or road extraction. There is a growing urge to define a set of transferable rules and concepts which can be implemented on multiple scales and objects. This would allow other scientific disciplines (medical, archaeological, etc.) to use the same methodologies without the need to create new method for every specific object. It would open doors for creation of special software packages which could then be used in almost all scientific fields interested in object delineation from point cloud.

4. FUTURE GOALS/CONCLUSION

»Today's scientists have substituted mathematics for experiments, and they wander off through equation after equation, and eventually build a structure which has no relation to reality.« Nikola Tesla

OBIA has proved its usability when it comes to 2D remote sensing imagery. Scientists are now trying to transfer those rule sets to 3D space. Some of the rules are transferable with editing but others need a complete revision. Two general approaches, the bottom-up approach and the top-down approach need to be tested to see which one is more useful for the area of implementing OBIA in 3D space. This should be the starting point for further research done by the author of this article.

Methodology needs to be defined on a general scale and approach. Rules need to be transferable between different scientific disciplines which have the need of extracting tangible information from the point clouds. Progress is promising so far; it shows that it is possible to extract objects directly from the 3d point cloud. Extracted objects are not just abstract forms; they can be used in further data analysis. It is possible to extract roads, trees and buildings in a semi- or fully-automated process and by doing so, preserve valuable time in processing the data. Additional work can be done in the field of improving algorithms but, as mentioned before, progress is so far promising. The author would once more like to stress the fact that a general approach is needed if we wish to come up with a completely transferable solution for object extraction from the point clouds.

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