Methods for quality improvement of multibeam and LiDAR point cloud data in the context of 3D surface reconstruction

Marek KULAWIAK, Zbigniew ŁUBNIEWSKI

Gdansk University of Technology
Faculty of Electronics, Telecommunications and Informatics
Department of Geoinformatics
Gdansk, Narutowicza 11/12, Poland
Marek.Kulawiak@eti.pg.gda.pl
Zbigniew.Lubniewski@eti.pg.gda.pl

Point cloud dataset is the transitional data model used in several marine and land remote-sensing applications. During further steps of processing, the transformation of point cloud spatial data to more complex models containing higher order geometric structures like edges and facets may be possible, if an appropriate quality level of input data is provided. Point cloud datasets usually contain a considerable amount of undesirable irregularities, such as strong variability of local point density, missing data, overlapping points and noise caused by scattering characteristics of the environment. For these reasons, processing such data can be quite problematic, especially in the field of object detection and three-dimensional surface reconstruction. This paper is focused on applying the proposed methods for reducing the mentioned irregularities from several datasets containing 3D point clouds acquired by multibeam sonars and LiDAR scanners. The article also presents the results obtained by each method, and discusses their advantages.

Keywords: multibeam sonar, LiDAR, 3D, point cloud, shape reconstruction, noise reduction

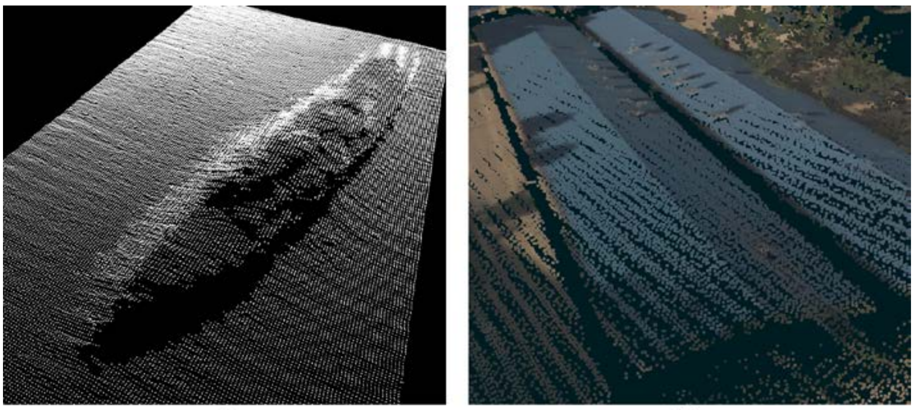
1. Introduction

Multibeam sonars and Light Detection And Ranging (LiDAR) systems are a major source of three-dimensional data available in the form of point clouds, used in several marine and land remote-sensing applications. The marine remote-sensing application example may be the high resolution bathymetry measurement, as well as measurement, detecting and visualization of underwater objects like shipwrecks. The land application example may be generating 3D models representing buildings and other terrain topography objects.

Unfortunately, the quality of point cloud datasets can suffer from various sources of distortion; such as ones caused by scattering characteristics of the environment, as well as by interference from unwanted objects or self-radiated noise coming from the vehicle used as a measurement platform. The presence of distortion can significantly affect the final results of processing such data, especially in the field of object detection and three-dimensional shape reconstruction. In this context, the paper presents several pre-processing methods of point cloud data which influence the performance of further reconstruction of three-dimensional meshes.

2. Description of the problem

Many methods have been proposed for solving the problem of surface reconstruction from point clouds, which can be classified into two categories depending on the complexity of the input data. The first category represents algorithms designed to process fully three-dimensional point sets, such as the popular Poisson reconstruction method [1], as well as the Ball-Pivoting [2] and the Power Crust [3] algorithms. The methods of the other category are mostly restricted to point sets located in two-dimensional space, such as the Delaunay triangulation [4], as well as various algorithms for creating height maps [5]. Since the structure of data obtained by multibeam sonars and LiDAR systems is often similar to 2D rasters (Fig. 1), the methods for two-dimensional shape reconstruction can be applied to them after performing several pre-processing steps, which will remove some of the unwanted features, such as noise. The existing solutions for decreasing the amount of distortion in three-dimensional point sets include methods such as [6] which attempt to simplify the entire input dataset while preserving sharp edges, as well as [7], which is based on dividing the data into a 3D grid of clusters, approximating the local shape of objects in each cluster, and removing points located far from those shapes.



a) b)

Fig. 1. Sample point cloud data obtained by a multibeam echosounder (a) and a LiDAR system (b)

Unfortunately, the existing methods used for reducing the amount of noise present in point clouds are mainly focused on removing various irregularities from dense datasets describing objects measured from many sides. Since the data is measured by multibeam sonars and LiDAR systems mostly from a single point of view, which is the common initial point for a set of beams or light rays, and therefore it is incomplete, the number of points marked for deletion should be kept at a minimum in order to preserve as much information as possible. Because of this, the data should be processed using methods designed for reducing specific types of distortion and may be converted into the form of regular rasters. After that, different triangulation algorithms can be applied to processed datasets. Several methods for solving the problem of denoising data obtained by multibeam sonars and LiDAR systems are proposed in the following section.

3. The processing methods

Three types of problems are taken into account in order to convert properly the input data into the form of a regular grid of points. The first and most common problem is the existence of holes in some areas. The suggested approach is to introduce new points in these regions with their heights either copied directly from the closest non-empty points, or calculated by interpolating proper values between existing points located near the processed hole. This operation is performed during many stages of the entire conversion process, as some of the other methods may actually increase the number of holes in the data in order to minimize the overall amount of distortions. One of such situations is presented in Fig. 2, where a sample point set shown in Fig. 2a), consisting of parallel lines of points (i.e. a fragment of multibeam bathymetry measurement output where each line may consist of a different number of points), is converted into a regular two-dimensional grid of heights shown in Fig. 2b). In this case, the positions of existing points are shifted so they are located at regular space intervals, while the height of each newly introduced point P is calculated by the means of linear interpolation using the following equation:

$$P_h = A_h((B_i - P_i) / (B_i - A_i)) + B_h((P_i - A_i) / (B_i - A_i)) \qquad (1)$$

where:
P_h – *height of the newly generated point P,*
A_h , B_h – *heights of points A and B being the nearest non-empty neighbour points of P located on the same list,*
A_i, B_i, P_i – *array indices of points A, B and P,* $A_i , B_i, P_i \geq 0,\ P_i > A_i ,\ B_i > P_i.$

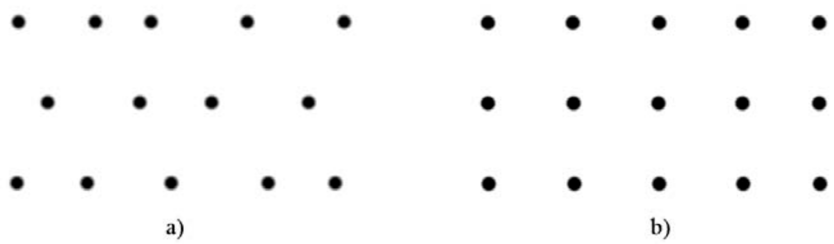
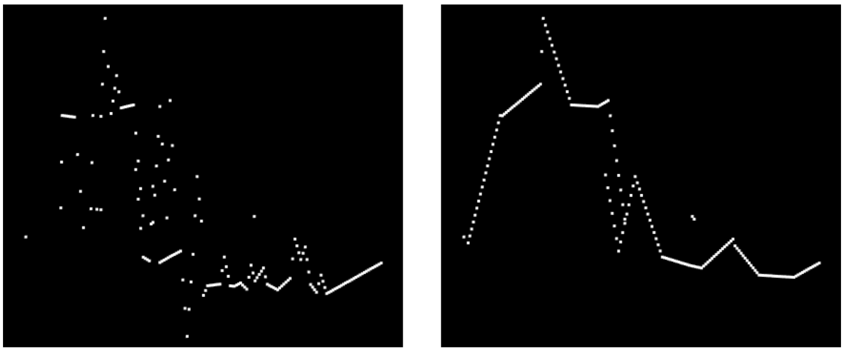


Fig. 2. An example of conversion from irregular point cloud data to regular raster.

The second type of problem is when the amount of noise in some areas is so high that the reconstruction process for these parts would create surfaces of undesirable shape, thus some amount of simplification is required. The proposed solution, the so-called “envelope filter” is to divide the distorted fragments of the data into small groups of points and preserve only the highest (i.e. with the highest *Z* coordinate value) points from each group so that they would describe the approximate shape of the outer surface of the data. New points are then generated in the place of the removed ones, using the same equation as described in (1), in order to make the data structure more regular. The application of this approach is shown in Fig. 3, where Fig. 3a) presents the unfiltered version of the swath featuring a lot of distortion, while Fig. 3b) shows the results of applying the envelope filter to the swath, causing the removal of the inner points.



a) b)

Fig. 3. A single multibeam swath featuring points which describe a fragment of a shipwreck

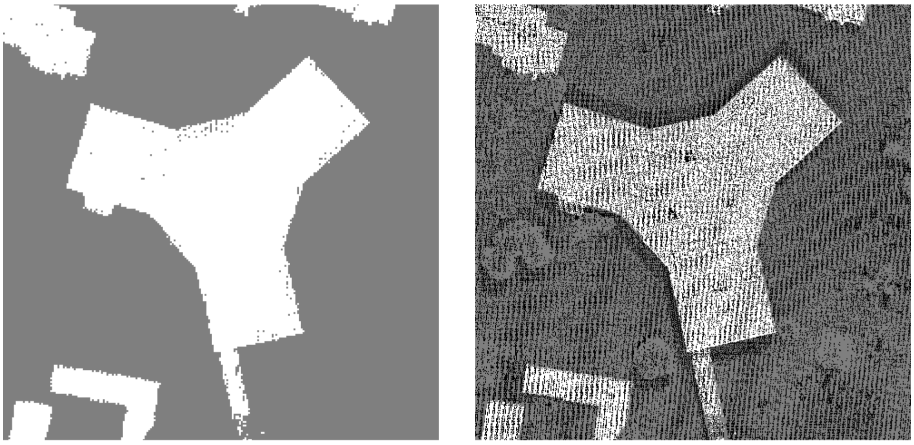
The last type of problem occurs when the input datasets have a strong variability of local point density. This situation can occur in either one dimension (when the data is organized in parallel lists of points, but the number of points per list is not constant) or in two dimensions. In the first case the solution is straightforward, and involves shifting existing points in each list so they become located at regular space intervals, and filling any holes created in this process (as presented earlier in this section). However, if the data structure is irregular with respect to two dimensions, a different approach is needed. First the dataset is divided into a regular grid of 2D sectors, where each sector contains up to several points. Each sector is then used to represent these points as a pixel in the output raster using the following procedure:

for each sector S_i :
BestClass = ID of the class which has most members in S_i ;
BestClassSize = number of points in S_i assigned to BestClass;
PointHeight = 0;
for each point P_i in S_i assigned to BestClass:
PointHeight = PointHeight + height of P_i ;
PointHeight = PointHeight / BestClassSize;

If a sector does not contain any points, it will result in a hole in the output dataset which can be replaced with a new point. One of the possible methods of doing so is using a procedure similar to the previous one:

for each empty point P_i :
Neighbours = a list of closest non-empty point neighbours of P_i ;
BestClass = ID of the class which has most members in Neighbours;
BestClassSize = number of points in Neighbours assigned to BestClass;
PointHeight = 0;
for each point N_i in Neighbours assigned to BestClass:
PointHeight = PointHeight + height of N_i ;
PointHeight = PointHeight / BestClassSize;

One of the more challenging tasks in this approach is determining the optimal resolution of the output dataset, i.e. the single pixel size. If the number of output pixels, i.e. their spatial resolution is too high, then the conversion process will result in data containing many holes, which will look inappropriate if their number is too high. On the other hand, decreasing the resolution too much may cause the removal of some important features from the data. The example of two results of converting the same pre-classified dataset of irregular points into a raster image is shown in Fig. 4, where buildings are visualised in white, ground and vegetation are shown in grey, and the missing data are represented by black colour. The original dataset in this example consisted of 274 thousand points representing an area of 14 thousand square metres. Fig. 4a) presents the converted dataset where each pixel represents a square with dimensions of 0.5×0.5 meters, resulting in an image consisting of 58 thousand pixels where approximately 2% of the output image pixels have been replaced with generated non-empty points. Fig. 4b) describes the converted dataset consisting of 230 thousand pixels, where each pixel represents a square with dimensions equal to 0.25×0.25 meters and approximately 36% of the image's pixels represent empty points in this case.



a) b)

Fig. 4. Two different results of converting a point set representing the classification information into raster image. Each grey level represents a different class (see the text above for details).

4. Results

This section presents the results of applying 2D triangulation algorithms to several datasets which were processed using methods dedicated to reducing the noise and other unwanted irregularities described above. The presented results confirm the importance of applying the appropriate point cloud data pre-processing method prior to utilising the 3D shape reconstruction procedure, i.e. the triangulation.

Fig. 5 compares the results of applying shape reconstruction to a sample point cloud containing a shipwreck multibeam measurement data consisting of 14 thousand points. Fig. 5a) and Fig. 5b) describe the contents of the same object, where the envelope filter was applied to the dataset shown in Fig. 5a). Fig. 5c) shows the result of creating a 3D model from the filtered data shown in picture Fig. 5a), while Fig. 5d) shows the result of generating a 3D model from the data shown in Fig. 5b).

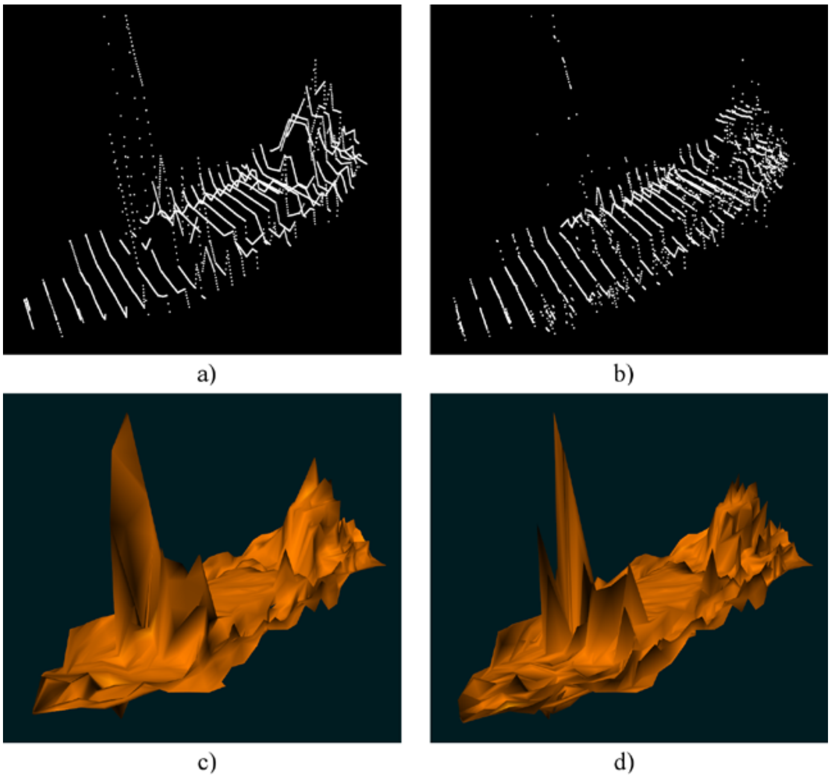


Fig. 5. The results of applying 2D shape reconstruction of a sample shipwreck. 3D shape reconstruction of a sample shipwreck

Fig. 6 compares the results of reconstructing the shape of a building from the previously described LiDAR raster data with the use of two-dimensional triangulation algorithms, and proper pre-processing methods. Fig. 6a) shows the result obtained from data pre-processed by the correctly chosen method, and its parameters, while Fig. 6b) presents the result obtained with applying the improper pre-processing of data.

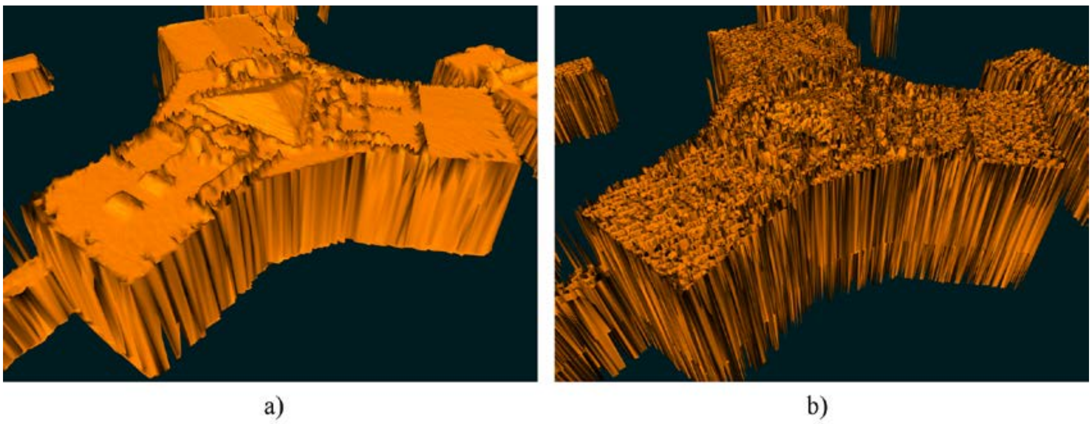


Fig. 6. Reconstructing the shape of a building from raster data originating from LiDAR measurements, with the use of two-dimensional triangulation algorithm

5. Conclusions

The article presents the proposed methods for reducing the unwanted noise, which is usually present in datasets obtained by multibeam sonars and LiDAR systems, in a way that preserves important features. The presented results also show the importance of using the appropriate processing methods in order to improve the quality of meshes created further by surface reconstruction algorithms. It is additionally demonstrated that converting unstructured two-dimensional point clouds into 3D rasters is an acceptable solution as long as the optimal resolution of the output dataset is chosen. Unfortunately, it is also clear that the development of new, improved processing methods for point sets is still needed.

Acknowledgement

We would like to express our gratitude to Dr. Krzysztof Bikonis from the Department of Geoinformatics, Gdańsk University of Technology, for providing us with mutibeam data on shipwrecks and seafloor measurement, as well as the Polish Centre of Geodesic and Cartographic Documentation (CODGIK) for providing us with sample LiDAR datasets.

References

[1] M. Kazhdan, M. Bolitho, H. Hoppe, "Poisson Surface Reconstruction", Eurographics Symposium on Geometry Processing, 61-70, 2006.

[2] F. Bernardini, J. Mittleman, H. Ftushmeier, C. Silva, G. Taubin, "The Ball-Pivoting Algorithm for Surface Reconstruction", IEEE Transactions on Visualization and Computer Graphics, Vol. 5, No. 4, 349-359, 1999.

[3] N. Amenta, S. Choi, R. K. Kolluri, "The Power Crust", Proceedings of the sixth ACM symposium on solid modeling and applications, 249-266, 2001.

[4] V. J. D. Tsai, "Delaunay triangulations in TIN creation: an overview and a linear-time algorithm", International Journal of Geographical Information Systems, vol. 7 iss. 6, 501-524, 1993, DOI 10.1080/02693799308901979.

[5] M. Kulawiak, Z. Łubniewski, 3D imaging of underwater objects using multibeam data, Hydroacoustics, Vol. 17, 123-128, 2014.

[6] H. Benhabiles, O. Aubreton, H. Barki, H. Tabia, "Fast simplification with sharp feature preserving for 3D point clouds", Programming and Systems (ISPS), 47-52, 2013, DOI 10.1109/ISPS.2013.6581492.

[7] W. Huang, Y. Li, P. Wen, "Algorithm for 3D point cloud denoising", Third International Conference on Genetic and Evolutionary Computing, 574-577, 2009, DOI 10.1109/WGEC.2009.139.