Sliding window algorithm applied to M_{split} estimation for seasonal change detection from LiDAR data

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Abstract

Light Detection and Ranging (LiDAR) systems can be a valuable source of information about environmental changes over time. It might concern changes in surfaces of different objects caused by seasonal effects, e.g., vegetation cover, various surface or groundwater levels, or snow load. Having LiDAR data from different periods allows one to assess such changes. Considering the huge number of measurements within a point cloud, one should choose a suitable data processing method. Classical methods, including the least squares estimation, might often be enough. However, such methods cannot deal with outlying observations, which often disturb LiDAR measurements. One of the possible choices would be the M_{split} estimation, which proved applicable to the problems mentioned. Up to now, that estimation method has been applied to the whole observation set or to its parts if the surface (or profile) has a more complex shape. This paper is concerned with applying a sliding window algorithm to process airborne laser scanning point clouds to detect seasonal changes in two examples: river water level and vegetation cover height. Generally, the results confirm the applicability of the algorithm in M_{split} estimation. The outcomes seem more informative and reliable than those obtained from processing the whole data or its separate parts. For the sake of comparison, the chosen data were also processed using classical methods, i.e., the least squares estimation and M-estimation. It shows that M_{split} estimation might overperform such methods.

Keywords: Sliding window, M_{split} estimation, LiDAR data

1 Introduction

Light Detection and Ranging (LiDAR) systems are modern measurement facilities that can provide a huge number of observations in a relatively short time. The measurements usually create a dense point cloud. One can acquire such observations of the same object in different epochs, which makes the base for deformation or displacement analysis (e.g., Cabaleiro et al., 2015; Yang et al., 2017; Janicka et al., 2020). Terrestrial laser scanning (TLS) can be applied to the problem mentioned, especially when a scanner can be placed close to the object. On the contrary, the accuracy of the airborne systems (ALS) is usually not sufficient for deformation analysis of buildings or engineering structures (e.g., Hodgson and Bresnahan, 2004; Alkan and Karsidag, 2012; Tomljenovic et al., 2015; Ostrowski et al., 2018). However, it can be used to monitor more extensive ground or water movements (landslides or changing water levels). Notwithstanding, the use of LiDAR point clouds usually requires data processing. The procedures in question are used to model, e.g., ground surface, engineering structures, or their deformations, and are meant to make the final product more accurate, reliable, and informative. There are several different approaches for processing LiDAR data, from the most conventional (the least squares method (LS)) to more complex and advanced methods (e.g., OptD, RANSAC, or M_{split} estimation) (e.g., Schnabel et al., 2007; Błaszczak-Bąk et al., 2015; Błaszczak-Bąk et al., 2017; Li et al., 2017; Wyszkowska et al., 2021).

M_{split} estimation is the method that was designed as a development of M-estimation (Wiśniewski, 2009). The primary assumption of the method is that the observation set is an unknown mixture of realizations of (at least) two different random variables. Such an assumption leads to the split of the classical functional model into (at least) two competitive functional models (Wiśniewski, 2009, 2010). That makes the method unique and that is also a reason why M_{split} estimation has found many practical applications: heterogeneous data fusion (Tao, Li et al., 2024; Tao, Su et al., 2024), detection of unstable points in GNSS networks (Banimostafavi, Sharifi and Farzaneh, 2023), deformation analysis (e.g., Wiśniewski, 2009, 2010; Zienkiewicz et al., 2017; Wyszkowska and Duchnowski, 2019), direct identification of gross errors (Li et al., 2013), S-transformation (Nowel, 2019; Guo et al., 2020), robust coordinate transformation (Janicka and Rapiński, 2013), marine navigation (e.g., Zienkiewicz and Czaplewski, 2017), regression analysis (Wiśniewski, 2009, 2010), or the most interesting here laser data processing (e.g., Błaszczak-Bąk et al., 2015; Janicka et al., 2020; Wyszkowska et al., 2021; Wyszkowska and Duchnowski, 2022; Janicka et al., 2023).

M_{split} estimation is, in fact, a class of estimation methods derived from different assumptions, which reflects the variety of applications in surveying or differences in observation set types to be processed. The basic variant of M_{split} estimation is the squared M_{split} estimation (SMS), and it is based on the general assumption that the observation errors are normally distributed (Wiśniewski, 2009, 2010). It is the simplest variant of M_{split} estimation. The second basic variant of M_{split} estimation is called the absolute M_{split} estimation (AMS), and it is based on applying L_1 norm condition (Wyszkowska and Duchnowski, 2019). There are also other variants of M_{split} estimation, e.g., variants that are robust against global or local outliers (Wyszkowska and Duchnowski, 2022, 2024).

2 Modelling from LiDAR data using M_{split} estimation

LiDAR data might be processed to obtain surfaces, profiles, or displacements or, generally, modelling actual terrain, engineering structures, or natural phenomena. In this paper, one can focus on the cutouts of the original point clouds related to the required profiles (e.g., terrain, water surface, or construction beam). The determined profiles are supposed to be approximated by polynomials of different degrees. The choice of the polynomial degree depends on the complexity of the profile. There are also various approaches to processing LiDAR data. The first one is to process all measurements together to obtain the entire profile at once. Such an approach can be associated with easy computations but is unsuitable for complex objects. The second approach divides the data into packs corresponding to the chosen profile parts. Then, each part is processed separately and can be performed in intervals of arbitrary distances. For example, one can assume 10 m distance intervals within the profile heights are estimated in the middle of the intervals. The subsequent observation sets do not have common points (e.g., Wyszkowska et al., 2021; Wyszkowska and Duchnowski, 2022).

This paper is focused on the third approach, namely the sliding window method. Here, one can assume the reasonable width of the sliding window. Such a window is then shifted from the beginning till the end of the profile by the chosen slide. The profile heights are determined in the middle of each window. The question is if such an approach can provide better (more reliable) results than the two classical approaches described in the preceding paragraph.

In this paper, the mentioned estimated heights at the chosen distances are obtained by applying different methods, i.e., SMS and AMS estimations (characteristic functions and appropriate algorithms can be found in Wiśniewski, 2009; Wyszkowska and Duchnowski, 2019) as well as the LS estimation and two robust M-estimation method, namely Huber method and Tukey method (more information about robust M-estimation can be found in e.g., Gui and Zhang, 1998; Ge et al., 2013). The estimated heights mentioned allow us to create estimated profiles for two different years, hence the profile of the height differences.

The comparison of all methods mentioned and the three approaches (processing whole sets, intervals, or sliding window method) are based on two real objects measured by ALS in two epochs (two different years).

3 Results

One assumes the same parameters for data processing for both objects. Each set concerns the profile of a length of 100 m. In the second approach, one creates nine intervals of the length of 10 m (from 5 m to 15 m, from 15 m to 25 m, etc.). In the third approach, the sliding window length is 20 m, and the slide of the window is equal to 10 m. More information about sliding window algorithm and applications can be found in (e.g., Wang et al., 2016; Li et al., 2018).

3.1 Field area

The first object is a field area near Malbork in Poland. Data from 2022 and 2023 were downloaded from https://www.geoportal.gov.pl/ (accessed on 9th July 2024). The cutout of the original LiDAR point cloud related to distance *d* of 100 m is presented in Figure 1 (*H* is a point height).

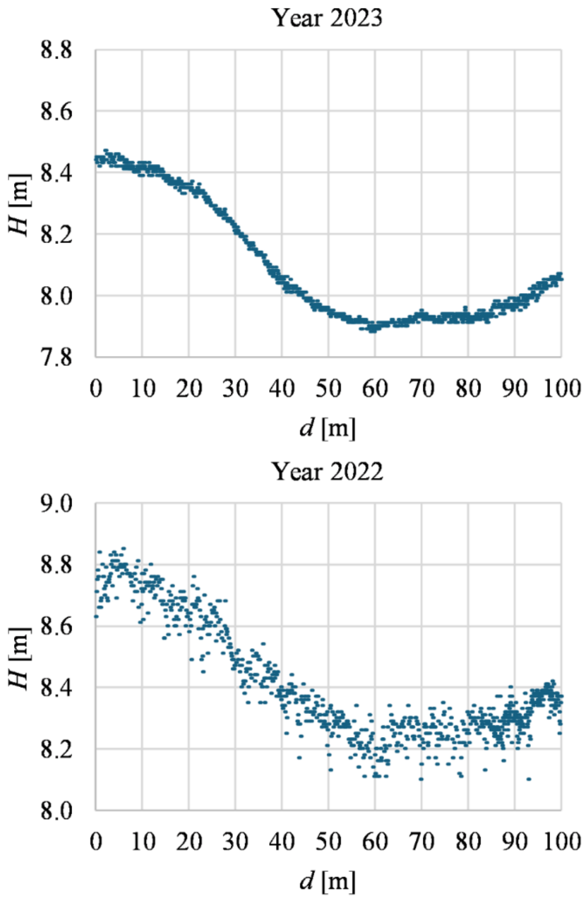

Figure 1. LiDAR data related to the field area

The data from each year are processed separately using the methods discussed and in three scenarios:

- Scenario A – each profile was approximated by the fourth-degree polynomial,
- Scenario B – 10 m intervals, in which estimated heights are determined by the second-degree polynomial,
- Scenario C – 20 m sliding windows, in which estimated heights are determined by the second-degree polynomial.

Figure 2 shows the height differences $\Delta\hat{H}$ for three scenarios.

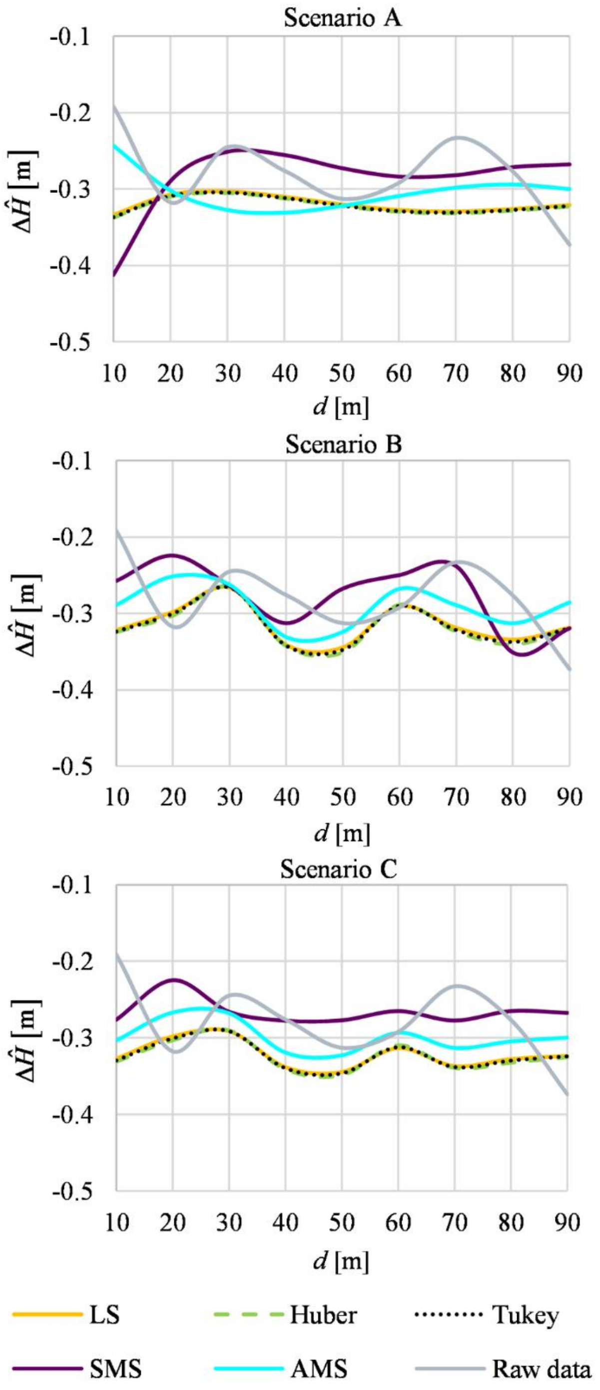

Figure 2. Estimated height differences $\Delta\hat{H}$ of the field area in different scenarios

The estimated height differences $\Delta\hat{H} = \hat{H}_{2023} - \hat{H}_{2022}$ (where $\hat{H}_{2023}$ is the estimated height in the year 2023 while $\hat{H}_{2022}$ in the year 2022) at every 10 m are obtained by applying SMS, AMS, LS, Huber, and Tukey estimations, respectively. In comparison, height differences are also based on raw data (obtained using linear interpolation at the same distances).

The simple graphical analysis reveals that data from 2022 are much less accurate than data from 2023, which stems from the change in measurement seasons. The older observation set is undoubtedly disturbed by the vegetation cover. It is also confirmed by the estimated differences in the profile (Fig. 2). The results of the methods applied differ significantly in the two first Scenarios. In the last Scenario, they are much more similar in shape. M_{split} estimation (both variants) provides smaller height differences, which might stem from higher robustness against the negative outliers.

3.2 River area

The second object is the Nogat River area near Malbork, Poland. Data from 2022 and 2023 were downloaded from https://www.geoportal.gov.pl/ (accessed on 9th July 2024). The cutout of the original LiDAR point cloud related to distance *d* of 100 m is presented in Figure 3.

Since in this test, one estimates the change of the water level in the river, the following slightly different scenarios are considered:

- Scenario A – each profile was approximated by the first-degree polynomial,
- Scenario B – 10 m intervals, in which estimated heights are determined by the first-degree polynomial,
- Scenario C – 20 m sliding windows, in which estimated heights are determined by the first-degree polynomial.

Figure 4 shows the height differences $\Delta\hat{H}$ for the river area in the three scenarios mentioned. The estimation results are the smoothest in the first Scenario. They seem to reflect the natural shape of the river. However, they “lost” the anomaly placed in the last 20 m distance under the study. Such an anomaly might result from waves or floating objects and should not be neglected in the analysis. It is well identified in the results of Scenarios B and C. The last Scenario, once again, brings results similar to one another in shape.

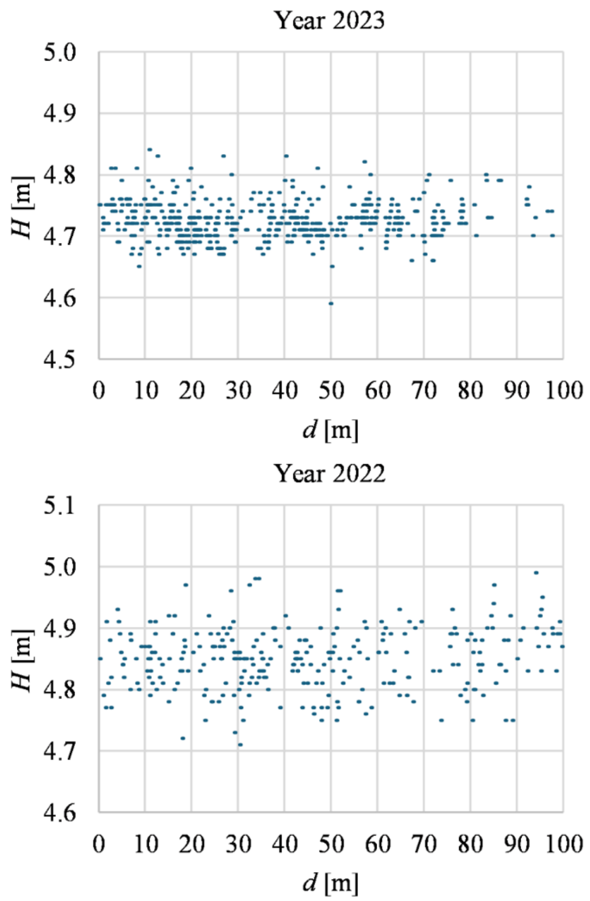

Figure 3. LiDAR data related to the river area

4 Conclusions

The study presented is preliminary research concerning applying the sliding window method in processing LiDAR data using M_{split} estimation. The results obtained for two example objects show that the approach mentioned brings more reliable results than processing the whole observation set or its parts excluding each other. Such general information is a clue for further research concerning the more detailed analysis of the method, especially from a practical point of view. There is no doubt that one should examine the optimal width of the window and the slide size. The results presented for the profiles are very promising. Therefore, the same approach might also be successful in estimating changes in whole surfaces. Such application is the subject of our next research.

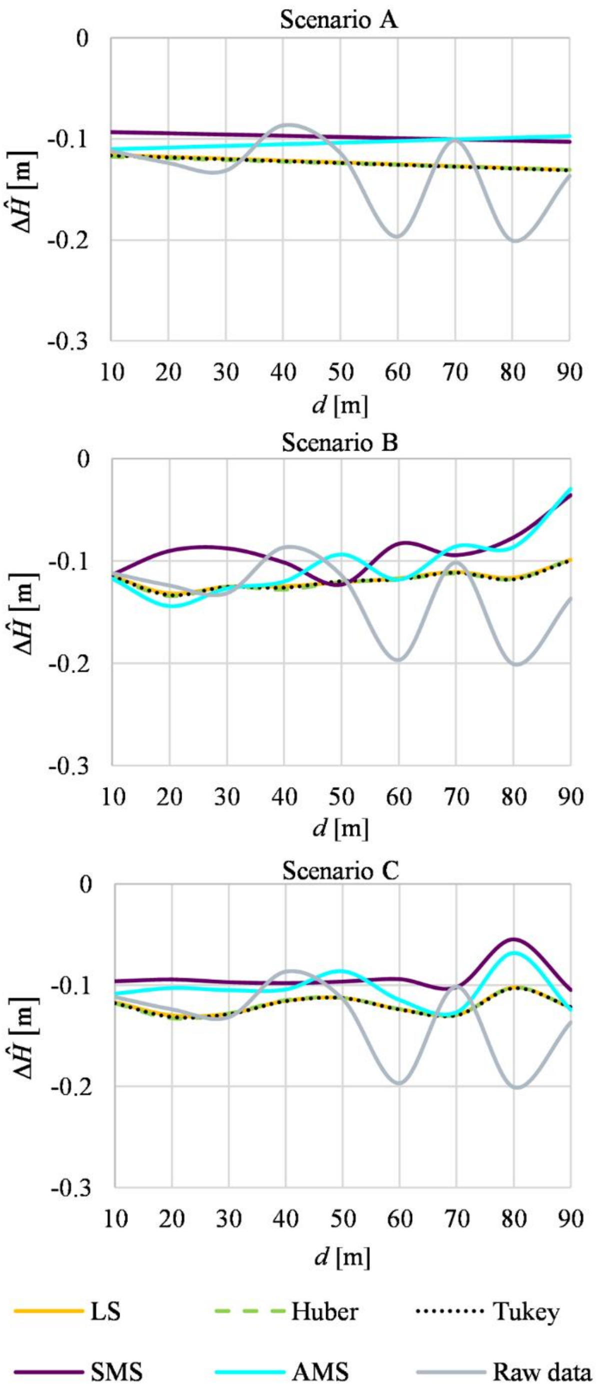

Figure 4. Estimated height differences $\Delta\hat{H}$ of the river area in different scenarios

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