Comparison of low-altitude UAV photogrammetry with terrestrial laser scanning as data-source methods for terrain covered in low vegetation

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**A B S T R A C T**

This article juxtaposes results from an unmanned aerial vehicle (UAV) and a terrestrial laser scanning (TLS) survey conducted to determine land relief. The determination of terrain relief is a task that requires precision in order to, for example, map natural and anthropogenic uplifts and subsides of the land surface. One of the problems encountered when using either method to determine relief is the impact of any vegetation covering the given site on the determination of the height of the site’s surface. In the discussed case, the site was covered mostly in low vegetation (grass). In one part, it had been mowed, whereas in the other it was 30–40 cm high. An attempt was made to filter point clouds in such a way as to leave only those points that represented the land surface and to eliminate those whose height was substantially affected by the surrounding vegetation. The reference land surface was determined from dense measurements obtained by means of a tacheometer and a rod-mounted reflector. This method ensures that the impact of vegetation is minimized. A comparison of the obtained accuracy levels, costs and effort related to each method leads to the conclusion that it is more efficient to use UAV than to use TLS for dense land relief modeling.

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1. Introduction

Modern measurement technology enables fast, remote and dense measurement and determination of point coordinates, which in turn allows the development of detailed land relief models. Such models have many applications, some of which require terrain data from two or more series of measurements. Land relief models are used for construction plans or survey maps. They are also used to determine changes in the geometry of a site, identified as uplifts/subsides of the land surface caused by natural (e.g. landslide) or anthropogenic (e.g. mining) factors. A detailed relief map also enables the performance of many archaeological, hydrological and geological analyses (e.g. Bemis et al., 2014; Castillo et al., 2011; Chiabrando et al., 2011; Immerzeel et al., 2014; Mesas-Carrascosa et al., 2014; Niethammer et al., 2012).

Unfortunately, the quality of such land surface models is biased not only by inaccurate measurement and reference, but also by vegetation covering a given site. This is a factor that, to a greater or lesser extent, affects all surveying methods in which measurements are taken automatically at target, as opposed to at a beacon placed at a known level above ground as in the case of more traditional surveying techniques. This cannot be considered as a flaw since randomly located points are measured, which inevitably results in vegetation being surveyed too. The thicker the vegetation, the fewer points are measured directly on the land surface. In the discussed case, measurements taken of vegetation and not directly of the land surface are considered to be noise that should be filtered out as much as possible.

Since aerial and terrestrial laser scanning became available on the market, data from such sources has contributed notably to improving the quality of studies in various fields (e.g. geographic information systems, cartography, forestry, industry, spatial planning). Currently, there is a tendency to complement or even entirely replace that technology with unmanned aerial vehicles (UAV) bearing digital photographic cameras. This allows the generation of precise point clouds representing the land surface and existing infrastructure. However, data obtained by means of this technology remain unclassified and impaired by measurement noise, which clearly causes errors during any subsequent analysis. That is why many recent studies have tackled the issue of data filtering and classification.

Considering the particularities of data acquisition and filtering methods, we can distinguish between macro- and micro-scale
technologies. The macro-scale ones include aerial laser scanning (ALS) in particular, which is the focus of the majority of recent studies. One of the most common filtering methods is progressive TIN (triangulated irregular network) densification (PTD) (Zhang et al., 2003; Zhang and Lin, 2013). The algorithm operates in five main steps: (i) eliminating outliers in the data, (ii) specifying filtration parameters, (iii) selecting seed points, (iv) constructing the TIN and (v) iterative densification of the TIN. A different method for filtering data from a variably shaped terrain focuses on the curvature of the surface (Hua et al., 2014). Its authors propose that data from a variably shaped terrain focuses on the curvature of the surface (Hua et al., 2014). Its authors propose that points be classified in a multi-iterative process consisting of the creation of a data pyramid and taking account of the deflection parameter of individual cells belonging to a grid created for filtration. A multi-stage approach towards filtration is also applied by many other researchers (Mongus and Zalik, 2012; Véga et al., 2012). It has become standard practice to divide a surveyed site into a grid of squares (Hui et al., 2016) and to select points by taking account of their height as a filtration parameter. In the case of urban point-cloud segmentation, one can additionally assume that in an urban landscape there exist a large number of typical architectural planes (Kim et al., 2016). In such a situation, one can perform point cloud selection by applying analysis of neighboring points, which includes the normal vectors of a surface fitted in the point cloud. This additional parameter accelerates analysis and offers an advantage when working on ALS or TLS (terrestrial laser scanning) data.

Point selection and classification algorithms are also applied in the micro-scale range, to both TLS and UAV data (Guarnieri et al., 2009; Panholzer and Prokop, 2013). They are mainly used in urban conditions to help create 3D models of the site surface and existing infrastructure. Researchers in this field (Weinmann et al., 2014, 2015) suggest a segmentation method that depends on geometrical features of individual point-cloud fragments. This concept is based on four main elements: (i) neighborhood selection, (ii) feature extraction, (iii) feature selection and (iv) classification. Its authors prefer to use a spherical range to look for neighboring points, and introduce the parameter k to indicate the number of included points. Next, sets of specific features defining the shape of a selected object are generated. The last step is based on a learning algorithm that classifies an entire cloud after random samples are entered. Some terrestrial scanners equipped with a receiver able to record a multi-return signal allow a classification similar to that used for ALS data. In such cases, a morphological filter (Hui et al., 2016) and a selection of final reflections can be used for classification (Pirotti et al., 2013). The applied filters are based on the progressive shift of a filtration window. A strategy that involves changing the size of the grid squares has been applied previously (Zhang et al., 2003). In this case, however, and in contradiction to earlier propositions, the authors suggest a gradual decrease in the size of the squares. Filtration consists in a gradual selection of the highest and lowest points in a given set and, based on that, performs segregation according to a chosen classification.

Data from UAVs equipped with digital cameras can also be filtered and selected by means of similar methods. This is especially important if one’s aim is to obtain results similar to those provided by the methods described above (Niethammer et al., 2012; Turner et al., 2015).

The case discussed herein differs slightly from those mentioned above. It concerns a site whose area is rather small and that is covered in low-growing vegetation. The key challenge is to minimize the impact of vegetation on the obtained land relief model in order to allow the survey results to be used to map terrain deformations (uplifts/subsidences). That is why this article does not deal with segmentation or classification (i.e. type recognition) questions, which are essential to the solutions offered by the algorithms in the quoted sources.

2. Materials and methods

An undeveloped, naturally formed and grass-covered slope located in the Upper Silesian Coal Basin was chosen as the testing site. The elevation difference between the lower, southern end of the site and the upper, northern end is about 14 m. The east-west inclination is much smaller. Fig. 1 shows a contour map of the testing site, including its division into two different vegetation zones. Most of the surveyed site was covered in relatively sparse and low-mowed (for the purposes of the survey) grass (A). However, part of the site had not been mowed and was covered in 30–40-cm tall grass (B); see Figs. 1 and 2. Only the northern part of the testing site (Fig. 1) was measured with use of a total station (see Section 3.1), so for the southern part of the site there is no reference survey.

The Upper Silesian Coal Basin has long been an area of underground mining. That is why its land geometry may change over time. Thus, the site had to be surveyed in short intervals in order to ensure that both the surface geometry and the vegetation remained unchanged, allowing a comparison of the results of different surveying methods.

2.1. Description of the survey

The site was surveyed over a few days using TLS, a UAV-borne system and a total station. All the measurements were connected...
to the same four control-network points determined with GNSS (global navigation satellite systems) and additionally tied by angular and linear observations. The relative position of the control points was determined with an accuracy of 2–3 mm for each of the N, E and H coordinates.

The experiment was conducted in order to determine the accuracy of the digital elevation model developed with the use of our own vegetation-filtration methods. A TLS survey of land covered in tall and dense vegetation would be pointless because the cover would prevent the development of a correct digital elevation model. Even when smooth, a point-cloud-based model does not represent the land surface, but only the top vegetation layer (Teza et al., 2007). Surveys by UAVs are also affected by vegetation covering a survey site. However, thanks to the orientation of the camera axis and the shooting of photographs from various positions, this is less of an issue for UAV surveys than it is for TLS surveys in the case of the type of vegetation being analyzed here.

For a couple of reasons, a reference survey was only conducted in the northern part of the site. First, this area was more morphologically heterogeneous and covered in both short and tall grass. Second, it was presumed that a partial survey would suffice for the purposes of the later analysis. It must also be kept in mind that taking such a detailed (Section 2.1.1) survey with traditional technology is laborious. Therefore, it was decided not to extend the model of the reference area beyond the dimensions necessary to facilitate analysis.

2.1.1. Reference survey

The reference survey was conducted using a Leica Nova MS-50 total station and a pole-mounted 360° prism. The chosen equipment and method allowed the survey to be completed in a short time without being affected by vegetation, an advantage that would not have been achieved in the case of direct mirrorless measurements. On the basis of the elementary error method and the instrument specification (Table 1), the accuracy of determining single points was estimated to be no worse than 1 cm in relation to the connecting points. Altogether, the method was used to determine the position of 1700 characteristic terrain points in an area of approximately 130 m × 110 m in the northern part of the site (Fig. 1). A terrain model for this part was created using linear interpolation. The accuracy of the model was lower than the accuracy of determining single points. The difference between the accuracy of a single point measurement and that of the model is caused by generalization, which is inevitable when applying this method.

2.1.2. UAV survey

A DJI S900 UAV system with a Sony ILCE-6000 camera mounted on a gimbal and equipped with a Sony SEL35F18 lens was used to approach the site and shoot photographs. The applied UAV was a hexacopter and the camera featured a 6000 × 4000–px APS-C sensor. The average flight altitude was 100 m above ground level, which allowed the camera and lens to cover an area of approximately 66 × 44 m with one photograph. Under such conditions, the GSD (ground sample distance) was about 11 mm.

During the horizontal flight, which covered a much larger area than did the tacheometry, a total of 230 photographs were taken. The side and forward overlaps were designed to be at least 50% and 70% respectively. These overlap values were chosen based on the highest part of the slope (above the northern part of the site). For the southern part of the site, the side and forward overlaps were larger (i.e. a minimum of 60% and 75%, respectively) because of the local inclination of the slope. Such overlap values were adopted in accordance with the analysis of the impact of the overlap size on the resulting products applied to the mapping of forest canopies (Dandois et al., 2015), which are much more complex structures spatially. The areas covered with shorter vegetation do not require the application of higher parameters. The UAV survey results did not reveal any errors that would indicate that the overlap values might have been chosen incorrectly.

In order to reference the UAV measurements, nine ground control points were distributed evenly over the photographed site were used. Four of these points constituted the control created for the multi-station survey (MS), whereas the other ones were determined using the MS. The data so obtained were processed with structure from motion (SFM) algorithms applied in the Agisoft PhotoScan Pro v. 1.1.6.2038 software. The camera calibration parameters were determined automatically during data processing. The RMS (root mean square) spatial error for the ground control points was 30 mm. The photographs were merged with the highest software settings (full scale of photographs), whereas the point cloud was generated with high settings (a quarter of the original image resolution). This approach was used to determine the positions of 58 million points over the whole site, including roughly 32 million points in its northern part, which was the part that had been surveyed with a tacheometer (Fig. 1). This translates into an average density of 2200 points/m² with a determined position. What is important is that the points are evenly distributed over the whole photographed site. The time dedicated to fieldwork did not exceed 2 h, including 1 h spent placing and measuring the ground control points.

2.1.3. Terrestrial laser scanning survey

A Leica ScanStation C10 scanner was used for TLS. The instrument uses a pulse method to measure distance at a rate of 50,000 points/s, and its scanning range is 134 m (with 18% albedo). The scanner has a 360° horizontal field of view and a 270° vertical field of view (−45° to +90°). That is why there are no points determined either under the scanner or in its vicinity from a given scanner set-up location. The whole site was surveyed from a total of 11 locations; its northern part, previously surveyed with a tacheometer, was surveyed from five locations. Only the part of the site with short grass was laser scanned. The few points scanned incidentally in the other part were not analyzed because their low density would have considerably distorted the results. The average distance between scanner set-up locations was approximately 45 m.
In order to perform registration, GNSS control-network points were used along with additional rotating black-and-white chequered reference targets mounted on tripods or placed on the ground surface. The average point-cloud registration error was 4 mm. This was calculated as a weighted mean of the differences in the location of the reference targets and the ‘cloud to cloud’ fitting between individual scans. The scanning density was set to 20 cm/100 m, and the scanning accuracy (the accuracy of determining scanned points in relation to the scanner set-up location) should be no worse than 6 mm according to the manufacturer. After taking account of connection and registration errors, the relative point-positioning errors did not exceed 10 mm.

Unlike the point cloud obtained by using the UAV, the TLS point cloud was not homogeneous. The point cloud density was correlated closely with the distance from the scanner set-up location. Altogether, the positions of 13 million points were determined over the whole site, including 6 million points in the area surveyed with the tacheometer. The average point density was 850 points/m². However, this figure is misleading because the degree of variation was large in this case, depending on the distance from the scanner set-up location. All the scanning-related tasks took 4 h and required two people.

2.2. Data processing

In order to minimize the impact of vegetation on the site elevation values determined on the basis of the UAV or TLS survey, a three-stage data-processing procedure was applied as described in the following subsections.

2.2.1. Processing, stage 1 – unification in a 5 × 5-cm grid

In the first stage, the analyzed site was divided into 5 × 5-cm grid cells, from each of which the lowest lying point was selected. The size of each cell was established arbitrarily on the assumptions that (i) a cell should be small enough to be considered relatively level and (ii) in an area of such size, vegetation-related measurement noise plays a bigger role than terrain inclination. Fig. 3 shows this stage of the data processing.

This operation allowed the unification (homogenization) of point clouds and a decrease in their density, while leaving in them the points that were essential to terrain surface modeling.

2.2.2. Processing, stage 2 – unification in a 25 × 25-cm grid

This stage of data unification is based on an assumption that the 25 × 25-cm areas can be approximated as planes without significantly distorting the real geometry of the land surface. This assumption has been made arbitrarily and means that smaller surface geometry irregularities will be generalized. Such filtration methods are commonly applied and have been described before (Chen et al., 2007; Kraus and Pfeifer, 1998; Thuy Vu and Tokunaga, 2004). They have even been implemented in a few programs used for the processing of ALS data, e.g. Fusion, SCOP++ and TerraScan. Nevertheless, this kind of filtration has been applied to TLS data only sporadically and to UAV data even more rarely.

The results of the previous stage constitute input data for this stage of processing. At this stage, processing starts by dividing the site into 25 × 25-cm cells and assigning to each cell points that are located therein. Next, the following algorithm is applied to each cell.

1. Multiple-regression plane fitting of points located in a given grid cell using the following equation:

\[ h(x, y) = a(x - x_s) + b(y - y_s) + c. \]

where \( a, b, c \) – sought plane equation coefficients, \( x, y \) – flat coordinates (explanatory variables), \( x_s, y_s \) –coordinates of the center of a 25 × 25-cm cell, \( h(x, y) \) – height of the plane for the \( x, y \) coordinates (response variable).

2. Calculation of the differences in height between points (data) and the plane in those points using the following equation:

\[ dH_i = h(x_i, y_i) - H(x_i, y_i). \]

where \( dH_i \) – difference in height between the fitted plane and the \( i \)th point, \( x_i, y_i \) –coordinates of the \( i \)th point, \( h(x_i, y_i) \) –height of the fitted plane for the \( x_i, y_i \) coordinates, \( H(x_i, y_i) \) –height of the \( i \)th point.

3. Selection of the lowest lying point in relation to the fitted plane, i.e. the point with the largest \( dH \) value. The other points in a cell are discarded and are not taken into account in the following stages.

Fig. 4 shows a diagram of this procedure.

2.2.3. Processing, stage 3 – filtration

Attenuating the remaining impact of vegetation is a rather challenging task. At this stage, the amount of data is still large (about 160,000 points in a 100 × 100-m area). This means that applying complex models that take into account all data would be very time consuming and/or require a lot of RAM. Therefore, the problem needs to be formulated in such a way that the solution will be based on local dependencies between points.

The result obtained in the previous stage was treated as an image. One pixel in this image corresponded to a 25 × 25-cm area, and its value (brightness) was the height of the single point that remained in this area after previous processing. This approach allows the direct application of digital image processing or more general signal analysis algorithms.

A review of UAV data after the first two processing stages revealed a considerable difference between data from the short-grass area (Fig. 1, zone A) and that from the tall-grass area (Fig. 1, zone B). At that point, data from the low-grass area were close to

Fig. 3. Diagram of stage 1 of processing: (a) division of the testing site into 5 × 5-cm cells; (b) points in a selected cell; (c) profile view with the selected lowest lying point; the other points are deleted and are not considered in the later stages of processing.
the reference survey values with few divergences. That proportion was somewhat contrary to the data from the high-grass area. Individual points were still close to reference values, but the majority were above the reference plane.

The tested filter left only those points whose heights were local minima. Unfortunately, this caused too much data thinning for short grass in some spots. As a result, the model developed through the interpolation of that data was too smooth and the model surface was below the reference surface. By contrast, the same filter applied to the tall-grass area proved to be more effective.

These observations led to the conclusion that in order to enable filtration, a surveyor must identify the areas of low and tall grass. An alternative approach requires the definition of a logical condition that would allow automatic differentiation between such areas.

A search for a criterion that would make the separation of those two cases (low vs. tall grass) possible led to the adoption of a threshold number of local minima in the area surrounding a given point. An attempt to optimize the number of local minima and the size of that area resulted in the acceptance of the following values: six local minima in a 4.25 × 4.25-m square (a window measuring 17 × 17 ‘pixels’). If the number of minima in an area was equal to or exceeded the threshold value, then a filter selecting only local minima was applied to that area. Otherwise, data obtained after the second stage of processing were used in the area. Fig. 5 illustrates the whole procedure, with its subsequent steps described below in this section.

Stage 3 processing algorithm:

1. Convert a point cloud obtained after the second stage of processing into an H matrix whose elements are point heights. The row and column (i,j) numbers of the matrix correspond to the row and column numbers of the 25 × 25-cm cells (i,j).

2. Determine local minima L for the whole site, where a local minimum is understood to be an element whose height is smaller than that of the element’s eight neighbors (an element lying also lower than elements on diagonals). The other points are rejected.

3. Create a C matrix with the following values:
   - C(i,j) = 1 if element L(i,j) exists (i.e. there is a local minimum in a cell)
   - C(i,j) = 0 if element L(i,j) does not exist (i.e. there is no local minimum in a cell)

4. Create an M matrix with the number of local minima in the neighborhood of each element (17 × 17-pixel window). For this purpose, a convolution of the C matrix with a 17 × 17 mask consisting of ones only was performed.

5. For each element of the matrix:
   - if M(i,j) > 6:
     - o if element L(i,j) exists, it is assigned to the result set,
     - o if element L(i,j) does not exist, there will be no point in the result set for such a cell,
   - if M(i,j) < 6, H(i,j) is placed in the result set.

6. Assign to the heights in the result matrix their respective x, y coordinates.

Fig. 6 provides a graphical representation of the selected algorithmic steps for the testing site.

3. Results

Accuracy analysis was performed only for the southern part of the site (see Fig. 1), where height values had been determined also by means of the tacheometer. This was because the tacheometric survey was designated as the reference one (as described in Section 2.1.1) in relation to which the errors of the determined heights (residues) would be calculated.

By means of this method, accuracy characteristics were determined for two types of data, namely the vertical distance of the model developed using the analyzed height determining method (UAV or TLS) in relation to (i) the direct height of the tacheometric survey points and (ii) the model developed using the tacheometric survey. All the digital elevation models were created by applying a linear interpolation method to a TIN composed of points surveyed using the total station.

Each of those two different approaches to the calculation of height errors has its own justification. Calculating errors in relation to actual measurement points is not affected by the generalization error of the interpolated model developed using the same points. That is why accuracy characteristics calculated in this way are more reliable, especially for smaller values. Therefore, this approach appears more appropriate than the other one. However, it must be noted that the tacheometric survey was conducted by measuring the prominent features of the land surface, i.e. usually points where the terrain inclination changed. From the point of view of terrain mapping by means of tacheometry, this is an entirely legitimate approach. However, the collected sample cannot be considered random as it was collected neither systematically (e.g. within a regular grid) nor completely randomly. Thus, the accuracy characteristics obtained by this method cannot be unreservedly considered as fully representative of the whole model.

Nevertheless, it is generally more pertinent to determine the error for the entire surface of a model rather than for only the prominent features of a site. For that reason, an attempt was made to determine the correspondence between the two models. The calculations were based on the divergence between the heights of points interpolated within a very dense 5 × 5-cm grid. It must be emphasized that both the reference tacheometric survey and the assessed UAV or TLS survey were interpolated. Therefore, the results of such an analysis are also affected by the generalization error of the model developed on the basis of the tacheometric survey but reflect the actual differences between the models more accurately. They also seem more useful for those who require this type of survey to determine vertical displacements (depressions/ elevations) in a site or to provide a general quality assessment of the mapped surface.
Fig. 5. Diagram representing the stage-3 processing algorithm for sample matrices (much smaller than actual ones).
Table 2 contains the RMS error values calculated from the raw data. The measurement noise (for UAV) associated with the vegetation covering the site is well reflected in the model profiles running along a selected line, as can be seen in Fig. 7 (see Fig. 1 for the position of the A–A profile). The vegetation issue is of course much more serious in the area covered with taller grass than it is in the area in which the grass had been mowed before the survey. The RMS error values listed in Table 2 clearly indicate that a UAV survey yields better results than those of a TLS survey. This should be attributed to the density and partly to the even distribution of the point cloud obtained with the UAV. It also seems that a significant effect is exerted by the UAV attaining a more favorable position in relation to the site during photographing than the scanner during measuring. This is closely related to the point of view of the surveying device. A bird’s-eye view grants many more opportunities to observe the actual surface of a site that is covered with low vegetation.

A comparison of the RMS values determined directly in relation to the total-station survey points with the RMS errors between the models in Table 2 (columns 3 and 4) clearly reveals the identity of those values. This proves first that the tacheometric survey was conducted properly, and second that there are no strongly divergent observations in the compared models. For this reason, in the following sections, only RMS error values determined directly in relation to the tacheometric survey points are presented.

### 3.1. Results, stage 1

The processed data and the resultant information were analyzed with attention paid to the following three aspects: (i) the coverage of the site with measurement points, (ii) the height difference between the highest and the lowest points in the 5 × 5-cm cells and (iii) the accuracy of the terrain height determination.

**Fig. 6.** Results of selected stage-3 processing steps for UAV: (a) local minima; (b) elements in the neighborhood (17 × 17) whose number of local minima is equal to or greater than 6 are black; (c) shaded relief interpolated from the result point set.

**Fig. 7.** Profile running along a selected line of the testing site from the UAV and tacheometric (reference) surveys.

**Table 2**

<table>
<thead>
<tr>
<th>Survey method</th>
<th>Vegetation</th>
<th>RMS tacheometry (mm)</th>
<th>RMS model (mm)</th>
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</thead>
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<td>Tall grass</td>
<td>119</td>
<td>123</td>
</tr>
<tr>
<td></td>
<td>Short grass</td>
<td>48</td>
<td>54</td>
</tr>
<tr>
<td>TLS</td>
<td>Short grass</td>
<td>124</td>
<td>117</td>
</tr>
</tbody>
</table>

**Fig. 8** shows the distribution of TLS survey points around of the scanner set-up locations in the southern part of the testing site (a) and a normalized histogram of points scanned by UAV and TLS (b). Both figures were created on the basis of the division of the horizontal surface into 5 × 5-cm cells. If one or more measurement points ended up in any of these cells, a pixel in Fig. 8(a) turned white; otherwise, it remained black. Similarly, the cardinality presented in Fig. 8(b) was determined in relation to the same cells. A dependence of the distribution of measured points on the scanner set-up location is evident. In the case of the UAV survey, the measurements are so dense and evenly distributed that only a few 5 × 5-cm cells are not covered with measurement points. That is why this image is not presented in the article. One immediately notes a very large percentage (nearly 60%) of 5 × 5-cm cells with no TLS measurement data. This is a disadvantageous condition for data filtration, for which a homogeneous coverage refines the results.

**Fig. 9** illustrates the distribution of the differences in height between the highest and the lowest points in the 5 × 5-cm cells...
for the UAV and TLS surveys. A dark pixel represents a difference in height equal to or greater than 10 cm. The darker the pixel, the greater the difference. A white pixel represents either no difference between the highest and lowest points measured in a cell or the measurement of at most one point in the cell.

In the case of UAV measurements, a greater variation in height in the $5 \times 5$-cm cells is evident in part B of the site (Fig. 9a); TLS did not yield reliable data for this area. However, we see a dependence of the height variation (max–min) in a cell on the distance from the scanner set-up location (Fig. 9b). We reason that this is related to both the density of the measured points and the sight-line incidence angle in the vicinity of the scanner. The laser beam has a higher chance of ‘hitting’ both the vegetation and the ground in one of the cells in the proximity of the scanner. The differences in heights within a cell reflect the data filtering effectiveness at this processing stage (the larger the differences, the greater the effectiveness).

The accuracy characteristics after the first stage of processing are presented in Table 3. Changes in the RMS errors from those for the raw data are almost negligible. This is illustrated in the last column, which lists the RMS error changes in relation to the raw data. This stage ensures an important reduction in measurement data density without any significant impairment of the accuracy of the models. This helps greatly to decrease the time required for the subsequent stages of data processing, since the volume of data presents serious challenges during the following analyses. What is more, the TLS measured points are distributed so unevenly that it impedes filtration. That is why decreasing data density variation is crucial, if not essential.

3.2. Results, stage 2

Table 4 lists the accuracy characteristics obtained on the basis of such thinned point clouds and of the models based on those clouds. The data clearly show that the RMS error for the TLS survey still tends to be about twice as large as for the UAV survey. Analysis of the relative changes in RMS errors leads to the conclusion that the second stage of data processing is effective for tall grass in the case of the UAV survey and for short grass in the case of the TLS survey. The only effect for short grass in the case of the UAV
survey was a decrease in the point cloud density. The accuracy of the model was not enhanced.

The size of grid squares applied in this case (25 × 25 cm) poses a risk of overgeneralization, which may lead to negative effects. However, as is shown by a comparative analysis against the reference data (Table 4), no overgeneralization occurred in this case and/or its impact on the height error was smaller than the positive effect related to reducing the noise due to vegetation.

3.3. Results, stage 3

Analysis of the RMS errors after the third stage of processing, listed in Table 5, indicates that the applied data processing was effective. A comparison of the survey methods shows that the UAV data are more accurate. One can observe a slight increase of the RMS error during the third stage of processing for short grass in the case of the UAV survey, a phenomenon that can be attributed to the imperfect logical condition used by the algorithm to differentiate between low and tall grass. This is due to the fact that, for certain combinations of measurement noise and terrain, the logical condition based on the number of local minima may cause the rejection (filtration) of points located on the terrain surface (Zhang et al., 2003). This means that if the terrain is formed locally in such a way that there are many minima in a filtered area, the filter will malfunction. However, the error values so obtained (Table 5) show that this does not happen often and does not cause any substantial decrease in the accuracy of the model. At the same time, the decrease in RMS error for tall grass during the third stage of processing is considerable, amounting to a third of the equivalent error after the previous two stages of processing. The effectiveness of the third stage of processing is much lower for TLS than it is for UAV. This should be attributed to the relatively low point-cloud density and the less favorable positioning of the surveying equipment (as compared to UAV), i.e. a worse line of sight. The results of the UAV data processing are also well illustrated in Fig. 10, which shows profiles interpolated from the UAV survey data and from the reference survey. Comparing Figs. 10 and 7 demonstrates clearly the effectiveness of the applied filtration method.

The juxtaposition of absolute raw-data residue values with processed data in Fig. 11 also provides a good summary of the application of the proposed UAV data processing. Absolute residue values equal to or greater than 30 cm are represented by dark pixels. The darker a pixel, the higher the absolute residue value. One pixel corresponds to a 5 × 5-cm area. In order to calculate the residues, linear interpolation was applied to obtain the heights at those points. Fig. 11(a) shows the absolute residue values for the raw data, whereas Fig. 11(b) shows the residue values for the filtered data. Fig. 11(c) shows the decrease in absolute residue values between (a) and (b), which is equivalent to the effectiveness of the filtration.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>RMS errors after stage 1 of processing.</th>
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<tbody>
<tr>
<td>Survey method</td>
<td>Vegetation</td>
</tr>
<tr>
<td>UAV</td>
<td>Tall grass</td>
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<tr>
<td></td>
<td>Short grass</td>
</tr>
<tr>
<td>TLS</td>
<td>Short grass</td>
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<tr>
<th>Table 4</th>
<th>RMS errors after stage 2 of processing.</th>
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<tbody>
<tr>
<td>Survey method</td>
<td>Vegetation</td>
</tr>
<tr>
<td>UAV</td>
<td>Tall grass</td>
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<tr>
<td></td>
<td>Short grass</td>
</tr>
<tr>
<td>TLS</td>
<td>Short grass</td>
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<tr>
<th>Table 5</th>
<th>RMS errors after stage 3 of processing.</th>
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<tr>
<td>Survey method</td>
<td>Vegetation</td>
</tr>
<tr>
<td>UAV</td>
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<td></td>
<td>Short grass</td>
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<td>TLS</td>
<td>Short grass</td>
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</table>

It is also evident here that the effectiveness is better for the area covered in higher grass. A similar dependence is characteristic for most filtration algorithms based on ALS data (Meng et al., 2010).

The median residual values after the third stage of processing are also of interest (see Table 6) because they reveal the average value by which the height of points should be changed to fit those points into reference heights (i.e. they can be identified with the values of the systematic error). There is a noticeably small negative median value for short grass in the case of the UAV survey. This shows that the heights so obtained are, in this case, virtually free of any systematic error related to vegetation and thus are affected almost exclusively by random errors. In the other cases, depending on the survey method, the median residual values are approximately 5 cm (UAV) and 7 cm (TLS).

Table 7 lists the numbers of UAV survey points making up the model in the northern part of the site (Fig. 1) at the consequent stages of the processing (i.e. points that were not filtered out). A continuous decrease is evident and, after three stages of processing, the number of points is about 480 times lower (nearly three orders of magnitude) than for the raw data. We emphasize that this is a desirable effect, especially in combination with a simultaneous decrease of the model error, as fewer data are easier to process. Reducing the amount of data not only reduces the working time of the algorithms but also decreases the required hard-drive storage space considerably (Liu et al., 2007).

An important feature of the proposed data-processing algorithm is its low sensitivity to the choice of the threshold of local minima, which is used to differentiate between short and tall grass. Fig. 12 shows the RMS error values for various local-minima thresholds.

4. Discussion

The accuracy of the raw data obtained via both survey methods (TLS and UAV) is comparable with that achieved in other research involving the application of those technologies. For TLS, this assess-
ment is based on the registration error value, whereas for UAV it is based on the accuracy of determining the position of points on the terrain surface covered in short grass. The accuracy level of registering the TLS scans was 10 mm as compared with 5–20 mm achieved in research conducted by Guarnieria et al. (2009) and Teza et al. (2007). The accuracy level of determining heights with UAV for short grass was 5 cm as compared with 4–7 cm achieved in research conducted by Turner et al. (2015). The accuracy level depending on the flight altitude and the applied equipment.

The rarefaction and unification of data density to 5 × 5-cm cells has a positive impact on the RMS error computed in relation both to points measured with a total station and (almost to the same degree) to a model developed on the basis of those points (for the UAV model, tall grass is 107 mm and short grass is 51 mm; for TLS, short grass is 106 mm). This means that no overgeneralization occurred, i.e. for the analyzed area, the 25 × 25-cm grid is not too rarefied and allows the relief to be mapped. The choice of the size of cells in which unification is performed should depend on a number of factors: the diversity of the terrain morphology, the density of measurement points, the accuracy of determining the height of points, and the unevenness of the density of the points (Chen et al., 2007; Meng et al., 2010; Serifoglu et al., 2016; Zhang et al., 2003).

The sequence of measures taken in connection with the first two processing steps (unification in 5 × 5-cm and 25 × 25-cm cells) is not random. The first processing stage corresponds to the use of only the last reflection for ALS data into the processing algorithm. Without this stage, the second processing stage would be significantly distorted by points located much above the ground (eg. trees). This is due to the fact that, at this stage, the regression method is employed, which is sensitive to outliers. Enhancing the effectiveness of this step by introducing a modification seems possible.

Such a modification would involve removing outliers before fitting a plane by regression. This would reduce the risk of incorrect determination of the plane and thus would also render the method more immune to gross errors. In the presented research, this problem did not occur because the ground was not covered in bushes or trees. However, the impact of this modification was not examined because it was presumed that its introduction would not enhance the processing effect significantly, given the terrain inclination and the vegetation cover.

The scholarly literature discusses two groups of data and methods of assessing the effectiveness of their filtration. The first one comprises ALS data (Meng et al., 2010; Mongus and Zálik, 2012; Zhang and Lin, 2013). In such papers, the effectiveness of a filter is measured as a percentage of correctly classified points located on the terrain surface. However, those papers do not provide information regarding the accuracy of determining the position or height of correctly classified points. Also, the density of point clouds is lower than one point per square meter. Because of these factors, any reference to the filtration results discussed in such articles seems out of place.

The second group of papers (Mesas-Carrascosa et al., 2014; Niethammer et al., 2012; Serifoglu et al., 2016) is concerned with the accuracy analysis of data obtained from UAV photogrammetry flights. Unfortunately, they do not discuss the problem of data noise due to vegetation and only mention sporadically the accuracy of determining the height of points. Usually, research in this area involves the determination of the accuracy of position (X, Y) on selected control points (GCP). The accuracy level of determining the position of those points was 4–6 cm, and of determining the height ca. 3–4 cm. The accuracy of those results is comparable with that achieved after the implementation of the proposed data-processing algorithm for short grass (ca. 5 cm) and for tall grass (ca. 7 cm).

Interestingly, a comparison of the reference survey with the UAV survey for tall grass yielded results that showed that the applied processing did not entirely eliminate the impact of the
grass (the median of the differences in the height of points was ca. 5 cm). On the one hand, this should encourage a search for better filtration algorithms. On the other hand, it may indicate a lack of points located on the terrain surface in many places.

5. Conclusions

The results described above need to be verified at a different site. They clearly show a considerable advantage in UAV photogrammetry over TLS at this kind of site. Applying TLS to the surveying of civil engineering sites and the high accuracy of point positioning offered by this method suggest it has an advantage over UAV in terms of accuracy. However, in the posed task, accuracy related only to the surveying method is less important than the position from which observations are made, a situation caused by the vegetation covering the site.

The discussed analyses enable the development of normalized digital elevation models. The execution of a procedure consisting of the subtraction of a digital elevation model generated from the described analyses from a land cover model will produce a result that indicates the height of the vegetation covering the surveyed site. Such data may be used to generate land cover and vegetation maps (Xue-Hua et al., 2002), which would enable various studies to be conducted, e.g. open-field seedling growth and survival measurements, vegetation growth measurements on land undergoing ecological restoration or hydrological research. The discussed filtration method could also be applied to assess the accuracy of data obtained by means of ALS or to support algorithms used for the classification of point clouds obtained by such methods (Bilskie and Hagen, 2013).

The performed analyses lead to the following conclusions.

1. The spatial distribution of UAV data was more even and thus more favorable than that of TLS data.
2. The first stage of the preliminary processing (division into $5 \times 5$-cm grid cells) did not significantly change the RMS error but clearly reduced the amount of data.
3. The second stage of the preliminary processing (division into $25 \times 25$-cm grid cells) had a greater effect on the model error and further reduced the amount of data.
4. The applied logical condition that automatically differentiated between low and tall grass areas on the basis of the number of local minima proved to be effective.
5. The applied data-processing procedure (stages 1–3) allowed the vegetation-related RMS error to be reduced by up to 25–40% depending on the survey method and the vegetation cover.
6. Analysis of the residue values in the tall grass area (UAV survey) indicated that, after the application of the proposed data-processing algorithm, the determined points were still 5–7 cm too high in relation to reference values (above ground).
7. The higher and denser the vegetation covering the land, the greater the impact of the filtration algorithm.
8. UAV photogrammetry proved to be more accurate than TLS when applied to terrain mapping. Furthermore, with equipment costs and surveying time taken into account, UAV turned out to be the more efficient method in this case.

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