SLAM AND INS BASED POSITIONAL ACCURACY ASSESSMENT OF NATURAL AND ARTIFICIAL OBJECTS UNDER THE FOREST CANOPY

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ABSTRACT:

The positional accuracy derived from the outputs of carried integrated devices was evaluated in this study. For data collection, the inertial navigation system (INS) SPAN NovAtel and a handheld mobile laser scanner GeoSLAM ZEB Horizon which uses simultaneous localization and mapping technology (SLAM) were utilized for data collection. The accuracy was assessed on the set of reference objects located under the forest canopy, which were measured via a traditional field survey (the methods of geodesy). In the results of this study the high potential of the devices and the application of data collection methods into forestry practice were pointed out. In our research, when the horizontal position of artificial entities was evaluated the average RMSE of 0.26 m, and the average positional RMSE of the derived natural objects (trees) was 0.09 m, both extracted from SLAM. The horizontal positional accuracy of trajectories with RMSE of 9.93 m (INS) and 0.40 m (SLAM) were accomplished.

1. INTRODUCTION

Presently, the Global Navigation Satellite Systems (GNSS) are the most frequently used positioning technology. Since this technology was applied in practical tasks, many innovations have been implemented, such as the modernization of equipment, software, or data evaluation algorithms. This improvement helped to integrate GNSS into commercial services. In contrast, positioning of objects and data collection within forest stands is predominantly performed in traditional ways. Traditional methods, electronic total station, and GNSS technology, which ensures the positioning of control points, bring several advantages and few difficulties in more complex conditions - straight line visibility, signal outages, and associated productivity reduction and unavoidable impact on the mapped environment (Gillet et al., 2000).

A comprehensive overview of the possibilities of using alternative methods for determining the position of objects was developed by (Keefe et al., 2019). Study is focused on the possibilities of using GNSS-based technologies in specialized and commonly used devices (ultra-broadband connections and radio telemetry, inertial navigation systems, simultaneous localization and mapping (SLAM), Bluetooth, RFID (radio frequency identification), QR code and others in real time with the use of postprocessing). The study describes the possibilities of using described methods to navigate moving objects, determine and share location of equipment, people, fish, animals, plants and even materials (e.g., air, water, fire) in forests.

Studies focused on GNSS in the forest environment have share common opinion that the mentioned technology can achieve accuracy varied from a few centimetres to several meters. It depends on number of factors such as the instrumentation, length of data observation period, and processing (Kaartinen et al., 2015). For example survey-grade receivers provide higher horizontal positioning accuracy than consumer-grade receivers (Danskin et al. 2009) and using differential computation and static observations was achieved centimetre-level accuracy, but open-sky conditions were required (Bakuła et al. 2015, 2009). A mobile device with two GPS receivers (navigation grade and survey grade) was tested under the forest canopy in a deciduous and a coniferous forest stand, mean stand tree heights 8.4 and 8.9 m, and reached the mean horizontal accuracy 4.1 m and 2.7 m (Tachiki et al., 2005). RMSE of 4.2–9.3 m for real-time 2D GNSS positions was reached and for an all-terrain vehicle with mounted GNSS/INS RMSE of 0.7m for 2D position (Kaartinen et al.. 2015). Therefore, the trend in the forest information gathering, is currently focused on the application of contactless devices and new technologies, ideally their combinations, and moves to the mobile devices.

An inertial navigation system (INS) is an autonomous system that does not depend on external information nor require energy from external space. They are therefore able to calculate the position, either with respect to a defined reference system/point or absolute coordinates (Gillet et al., 2000). INS are most effective in combination with GNSS devices. GNSS essentially requires an external input - a satellite signal. Accuracy in challenging environment is variable, depending on the number of satellites, their geometry, multipath effect etc. The technological combination makes it possible to bridge the gap in the GNSS signal and thus improve positional accuracy. The final integration is ensured by an algorithm for estimating quantities, called the Kalman filter and Tightly Coupled

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INS/GNSS Integration (Bonnor, 2014). Furthermore the study describes similarity between the forest environment and urban canyons, and the problem of reducing the number of visible and suitable satellites due to shading objects – crowns of trees (Qian et al., 2017). It causes the multipath effect and serious errors are registered. The basic algorithm and the overall related issues are intensively studied and developed (practical principles and theoretical background) in several studies (Hide et al., 2003; Lee et al., 2013; Wang et al., 2010; Welch and Bishop, 2006).

The terrestrial laser scanning (TLS) is an increasingly inflected term. In addition to the constant development of new applications aimed at expanding the range of measurements under specific conditions, technology is increasingly used in ecosystem research (Danson et al., 2018). Several authors have developed the issue of TLS in the forest environment (Chen et al., 2019; Hyyppä et al., 2020c, 2020b; James and Quinton, 2014; Liang et al., 2019, 2016; Tomaštík et al., 2017). Although TLS offers benefits such as high efficiency and productivity there is a growing demand for dynamic forest information gathering tools that make it more efficient in many ways. The TLS method is highly efficient in plot-level. Small circular area of forest with a radius aproximately 10 m is typical shape of permanent sample plot in natural forest inventories. Large areas data collection by the conventional measurement tools is expensive. Although TLS is viable option lack of mobility in challenging environment is a great obstacle (Xinlian Liang et al., 2014). This is the reason why the community investigate the potential and accuracy of the Mobile Laser Scanning (MLS) systems.

MLS techniques can be divided into phone-based scanning, vehicle-based scanning, Unmanned Aircraft Vehicle (UAV) - based, handheld (HMLS) and other personal laser scanning (PLS) techniques (Hyyppä et al., 2020b). Several authors analysed and studied the named methods; the accuracy and efficiency of UAV, TLS and MLS methods utilized in urban tree mapping and monitoring was evaluated in (Holopainen et al., 2013), also the usage of a mobile laser scanning system for mapping large forest plots and possibilities of PLS for forest mapping and ecosystem services were explored in (X Liang et al., 2014; Xinlian Liang et al., 2014). For automatic or semiautomatic ALS individual tree detection (ALSITDauto or ALSITDvisual) and manual or automatic measurements of TLS and MLS (TLSauto, MLSauto, MLSmanual, MLSsemi) 438 trees located in urban parks and forested environments were measured, mapped and compared with reference TLS data set (Holopainen et al., 2013). In the process of tree detection rate and location accuracy evaluation RMSE varied between 0.44 m and 1.57 m. The stem mapping accuracy 87.5% with RMSE of the location 0.28 m (RMSE of the diameter at breast height (DBH) estimation was 2.36 cm) was reached within the large forest plot mapping (X Liang et al., 2014), and with a multipass-corridor-mapping method for PLS data processing the tree stem detection accuracy 82.6% RMSE of the estimates of tree location was 0.38 m (RMSE of the DBH was 5.06 cm) from data collected on a 2,000 m^2 large forest plot (Xinlian Liang et al., 2014). Further, general results based on the examination of studies (Liang et al., 2015; Ryding et al., 2015) are available, the possibility to cover a 5ha research area in 15 minutes with MLS/PLS with stem mapping accuracy ranges between 80% and 92% with the DBH RMSE% varied between 8% and 29%, what is comparable with TLS multi-scan method with fixed radius at the same conditions (Liang et al., 2019). However, it reveals nothing about the location of the objects. With Google Tango technology for outdoor measurements in forest inventory tasks RMSE of the DBHs were up to two

centimetres, and RMSE positions were over one metre for the Spiral pattern and 0.20 m for the Sun pattern of data collection (Tomaštík et al., 2017). The position references were measured using a total station. In comparison with the calliper and tape measured data set, the usability of the Kinect and Google Tango depth sensors for tree stem mapping was shown, where Kinect-derived tree reached RMSE 1.90 cm and for Tango measurements RMSE 0.73 cm. Besides, the work sketches a question of possibility to measure the location of the trees which they would like to use as a reference - potential application of an assisted GNSS in 3D Game Engine based approach.

With using an in-house-built backpack laser scanner and GeoSLAM ZEB114 of the 18 trees were recognized, within 30 s duration of data collection on the 250 m^2 area (Oveland et al., 2017). The RMSE of the DBH varied between -1 cm and 3 cm when the automatic estimated of tree positions and stem diameter from MLS was imputed. Soon after, the three ground based laser measurement methods were compared (Oveland et al., 2018): TLS, HMLS and a backpack laser scanner (BPLS) with GNSS and total station made reference dataset. They achieved positional RMSE 82 cm (TLS), 20 cm (HMLS) and 62 cm (BPLS), as well as 6.2 cm (TLS), 3.1 cm (HMLS) and 2.2 cm (BPLS) RMSE of DBH estimation. During the stem detection and stem curve extraction from the under - canopy UAV laser scanning data (Hyyppä et al., 2020a) the one of the goals of mentioned study was described as alebo as follow: identification of points reflected from the tree trunk, where the tree positioning errors had to be taken into account (resulted from the movement of the laser scanner). It was still on the order of 10 cm or above. However, high-quality SLAM-system was integrated into composition.

The benefits of terrestrial laser scanning (data collection speed, high quality, wide applicability of data) is combined in SLAM technology. It meets high requirements for image quality of the recorded environment even in locations with low GNSS signal quality. In the application of SLAM technology to the forest environment, research has been moving forward in recent years. Many authors are exploring the possibilities of using this technological process in relation to the forest environment and various ecosystems, for example following the forestry work processes and navigation of logging and transport technologies (Nevalainen et al., 2020), in comparison with other mobile laser scanning technologies in boreal forest conditions (Hyyppä et al., 2020c),mobile robotics (Ali et al., 2020), autonomous research, and forestry. SLAM solutions in modern mapping devices are expected to improve measurement accuracy when the satellite signal is weak (Qian et al., 2017). From earlier studies, the usage of SLAM technology was examined in several works (James and Quinton, 2014; Ryding et al., 2015). They discuss about the HMLS ability to map complex environment approximately 40 times faster than TLS, and as fast as a photo-survey method, processed by structure from motion and multi-view stereo algorithms. Additionally, the ability to derive DBH comparable with TLS estimation was achieved (modelling success rate of 91 % with DBH > 10 cm).

Improvement of GNSS/INS reduced by forest stand features with application of the LiDAR-based SLAM technique is studied in the southern boreal forest zone (Qian et al., 2017). Results show the horizontal positioning accuracy of an entire trajectory of 800 m is 0.13 m. The another study presents the influence examination of scan density, when single tree attributes need to be estimated (Perugia et al., 2019). For the single-tree attributes assessment a10 m scan path provided the best results, with an omission error of 6% in pure *Castanea sativa* (Mill.) stands cultivated for fruit production. For reaching

a precision which complies with the accuracy standards for land survey, two types of SLAM devices were used (Chudá et al., 2020). Comparing with GNSS and total station measured data the RMSE of under-canopy object position were 25.3 cm and 28.4 cm. Two SLAM methods for odometry and mapping comparison was presented in (Nevalainen et al., 2020). Both methods present 85% agreement in registration within 15 m of the strip road and accuracy of odometry 0.5 m per 100 m. The device has been mounted on a harvester with a laser scanner and GNSS performing forest thinning. The pulse-based backpack laser scanner with in-house developed SLAM were utilized (Hyyppä et al., 2020b) when the derivation of stem curve and volume were examined. The positioning error of individual points is on the order of 10–20 cm after the SLAM algorithm application. The circle's coordinates in the TLS point cloud at the height of 1.3 m was basis for the reference tree position determination.

This paper is focused on the use of carried integrated devices under the vegetation cover and the subsequent evaluation of the accuracy of determining the position of objects when their position is automatically derived from the data products of the mentioned devices. In this paper, to obtain navigation solutions for trajectories under the forest canopy GNSS/INS data were used as well as solution produced by HMLS using SLAM technology. The image of the environment was recorded in the form of a point cloud created by HMLS, then natural and artificial objects were extracted from the point cloud. These objects were used for evaluation of the positional accuracy of the points recorded under the forest cover.

Goal of this paper is to verify the positional accuracy of objects under forest canopy measured with different approaches to data collection in non-ideal conditions, without the use of latest positioning kits designed for challenging environment. The area of interest was mapped by SLAM technology, according to the recommendations and results of our previous research, a procedure optimal for the forest environment. To evaluate performance of devices not consisting of an additional devices kit, and their essence and purpose is defined by the task.

2. MATERIAL AND METHODES

2.1 Study area

For the needs of this study, two similar tree composition stands were selected. The stands have different ages and different densities of individuals. During the selection of sites for research areas, we followed the visual assessment of the stands in the first step. The aim was to select localities which differs in the number of individuals and the difference in average DBH will increase twofold. Two localities with density 133 trees/ha (locality 1) and density 344 trees/ha (locality 2) were chosen (Figure 1). Two research sub-plots were established in each of the mentioned stand locality, in the shape of a square measuring 25 x 25 m (locality 1 – F, G; locality 2 – A, B). The corner points of the research plots were stabilized, marked, and measured by the total station. To establish a high accuracy, position the corner points was measured from the standpoints with ideal conditions for measurement by GNSS technology.
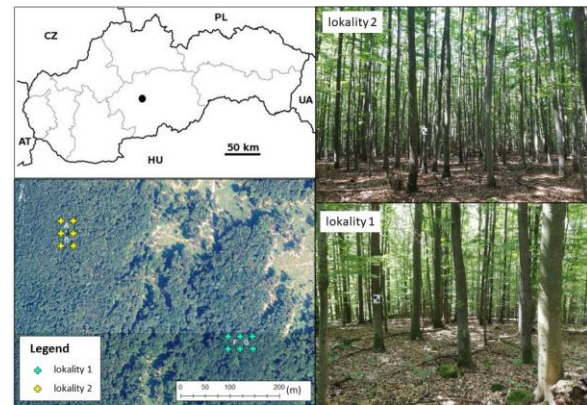

Figure 1. The research areas - a managed forest located in the Central Slovakia.

2.2 Reference data

The reference data were the centres of the upper walls of the cubes, distributed along the lines in the research area. The reference objects - cubes were placed in a checkerboard pattern throughout the research plots, in lines with regular spacing between objects and regular line intervals. Also, DBH of all trees was measured at the height of 1.3. with diameter tape. After measuring the DBH of all trees, we can state that the data collection sites were suitably differentiated, for research purposes. At the locality 1 there are 25 individuals in on sub-plot F with the average DBH 31.2 cm, and 55 individuals with an average DBH of 21.6 cm on the sub-plot G.

At the sub-plot A located in the locality 2 lies 98 individuals with an average DBH of 6.8 cm and at the sub-plot B 58 individuals with an average DBH value of 9.8 cm were measured.

2.3 Experimental data collection

To obtain navigation solutions for trajectories under the forest canopy, GNSS/INS data were collected by a NovAtel SPAN system and processed using the Waypoint Inertial Explorer software package. Simultaneously, to obtain the same trajectory and additional view of the environment the HMLS GeoSLAM ZEB Horizon with SLAM technology was used. It produces a point cloud with data acquisition 300 000 points/sec. with relative position accuracy 1 - 3 cm and maximum range of 100 m. The INS records data in the form of a trajectory which the device describe as a line of points. It was necessary to create reference point signallers over which it would be possible to cross with both devices. At the same time, it was necessary to use objects with the shape that is easy to identify in the point clouds acquired by SLAM device to calculate their centre coordinates. Also, the position of all trees, as well as DBH, were recorded the same way. Data collection took place simultaneously (Figure 2) with both devices at the same time to ensure the same conditions for all collection forms.

Figure 2. GeoSLAM ZEB Horizon and IMU backpack SPAN NovAtel during data collection.

The devices were carried in a uniform rectilinear motion across the research plots according to predefined schemes (Figure 3). The central points of both devices were carried above the reference object.
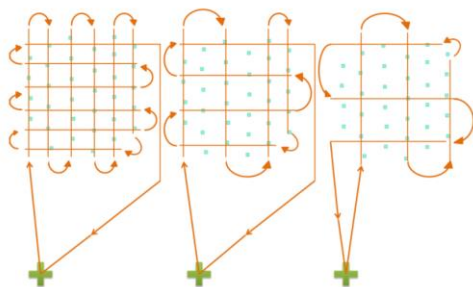

Figure 3. Schematic representation of the movement around the sub-plots - dense, medium, and sparse area coverage.

Three forms of data collection were accomplished. Depending on the intensity of the area covered and the number of turns during the data acquisition, they can be named as dense, medium, and sparse lines.

2.4 Data processing

INS data - files containing trajectory records – were processed in Waypoint Inertial Explorer software. The RINEX correction files adding was needed. Afterward, for data processing, the tightly coupled method could be used.

HMLS data were pre-processed directly in the field immediately after recording in GeoSLAM Hub as part of the data collection process when the algorithm evaluates and processes the recorded data. The next step was the transformation of point clouds into the S-JTSK coordinate system according to reference geodetic spheres placed at the corner points of the research areas. Their locations were measured as a part of the reference data collection process. The procedure for extraction and calculation of the position of the reference objects was as follows. For easier handling, point clouds were reduced to a height of 2 m above the ground. Then, based on a 20 cm distance zone around the reference objects (Figure 4), the cubes, and their immediate surroundings, were cut out of the point cloud.
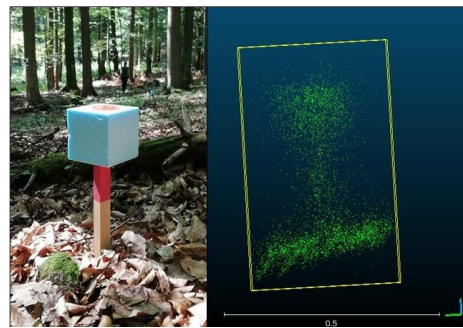

Figure 4. Reference artificial object.

The procedure for the diameter of trees derivation in the program DendroCloud 1.50, was described in more detail in several works (Chudá et al., 2020; Hunčaga et al., 2020; Koreň, 2019). Most parameters were left at predefined values. The thickness of the point clustered section was determined at five centimetres, concerning the overall dimensions of the cubes (Figure 5). The cross-section height was selected according to the place on the reference cube where the reference point was measured therefore the cross-section contained an area with the location of the reference point.
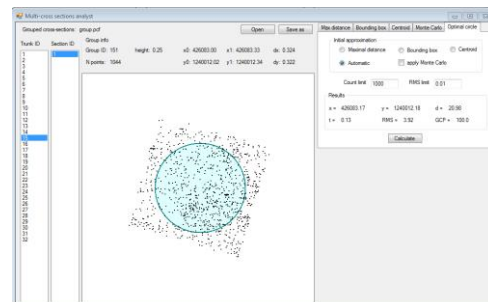

Figure 5. Example of the reference object position calculation.

Although the program is used primarily to derive stem thicknesses, the Centroid method derives the stem position as the arithmetic mean of the points of the spatial cluster. The radius is approximate by the mean distance of the points from the stem position. Due to the fact, in this case, it is not the radius that is important but the position, which was calculated as described above, the procedure was satisfactory.

The position of the trees was derived according to mentioned study, too. The resulting product is therefore a data set containing, in addition to data on the position of the trunk, its derived DBH.

In the case of creating pairs between reference and derived data from INS, we proceeded as follows: The basis for the work was the trajectory of the SLAM device and GPS time data from both devices. In the first step, we determined the zero point - the place at the beginning of the trajectories of both devices, when the operator was already in motion and the trajectories were visually as close to each other as is possible on the way there and on the way back from the stand. Because the HMLS device achieved very accurate results, we used data from it as a basis for processing. Based on GPS time data, we recorded the duration of data collection in seconds from the zero point until it is reached again. Subsequently, we converted the absolute values to relative, which gave us the answer to the question: when were both devices above the reference point. After finding the corresponding a relative value in the INS data, we were able to identify the reference data with the data from the INS trajectory. Thus, to obtain the coordinates of the points that

should have been above the reference object at a specific collection time and to calculate their differences with respect to the specific reference objects - cubes.

Preceding the evaluation of the data, a pair of reference and derived positions was identified. The maximum distance between position extracted from trajectories is 4.0 m so that a cube model from a neighbouring row cannot be assigned. The value is used for logical control and exclusion of inclusion of extremely remote values in the evaluated files. In the case of natural and artificial objects whose position was taken from a point cloud, the threshold value was 0.284 m.

2.5 Study methods

The experiment was focused on evaluating the accuracy of position determination of points derived from HMLS point clouds using SLAM technology and point clouds representing the trajectory of INS equipment. In the statistical evaluation of positional accuracy of point determination, we based on the principles of quantitative validation of value errors (Sedmák, 2009; Šmelko, 2015; Yang et al., 2004).

The following equations were used for the accuracy evaluation of the natural and artificial object positions extracted from point cloud, and for trajectory accuracy assessment.

$$e_{i(x)} = x_{ref} - x_{gen} \qquad (1)$$

$$e_{i(x)} = \frac{x_{ref} - x_{gen}}{x_{ref}} \cdot 100 \qquad (2)$$

$$\bar{e}_x = \frac{\sum e_{i(x)}}{n} \qquad (3)$$

$$s_{e_x} = \sqrt{\frac{\sum (e_{i(x)} - \bar{e})^2}{n-1}} \qquad (4)$$

$$RMSE_{(x)} = \sqrt{\frac{\sum e_{i(x)}^2}{n}} = \sqrt{\bar{e}_x^2 + s_{e_x}^2} \qquad (5)$$

$$MSE = \frac{\sum e_x^2}{n} + \frac{\sum e_y^2}{n} + \frac{\sum e_z^2}{n} \qquad (6)$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum e_x^2}{n} + \frac{\sum e_y^2}{n} + \frac{\sum e_z^2}{n}} \qquad (7)$$

Where: x, y, z = object coordinates (cubes/trees/trajectory points)
          n = number of identified cubes/trees/trajectory points
          s_e = standard deviation

The significance of position estimation errors was tested by one-way ANOVA with a post hoc Tukey HSD test in Statistica software (Statsoft Inc., Tulsa, OK, USA).

3. RESULTS

The following section presents the research results. For better appreciation of results, we present, the approximate travel distances for every data collection type: dense – 480 m, medium – 370 m, sparse – 360 m. The low difference between medium and sparse is caused by the fact that each research area had a different starting point for data collection to achieve optimal conditions for collection (free space without crowns). The time aspect, the positional accuracy of the objects extracted from point cloud (natural and artificial objects), the accuracy of the trajectories of the GeoSLAM ZEB Horizon device and the trajectories of the inertial navigation system SPAN NovAtel

were evaluated (Table 1). Testing of the statistical significance of the bias was performed with a One-sample T test (a 95% confidence level, p-value <0.001). For cases where the statistical significance of the systematic error was demonstrated in the evaluation of the differences calculated for the reference and derived coordinates in the direction of the X, Y and Z axes, we present the modified values a in parentheses.

Positional accuracy	Dimension	Average RMSE
artificial objects (cubes)	(2D) SLAM	0.26 (0.14) m
	(3D) SLAM	0.29 m
trajectory accuracy evaluated at artificial objects	(2D) INS - postp.	9.93 (9.185) m
	(2D) SLAM	0.13 m
	(3D) SLAM	0.40 (0.215) m
natural objects (trees)	(2D) SLAM	0.09 m
	(3D) SLAM	0.23 (0.215) m

Table 1. Results of positional accuracy assessment – average RMSE values (in parentheses - the values after counting out the systematic error).

3.1 Time

The time required is not high, as the collection lasted a maximum of 18 minutes and a minimum of 7 minutes (Table 2). With the planned and pre-marked direction of movement, the differences between sites of different characteristics are within a few minutes. The area coverage density affects the duration of data collection.

Locality I. (133 trees/ha)			
sub-plot	Duration for coverage intensity		
	dense	medium	sparse
F	15	11	?
G	16	18	8
Locality II. (344 trees/ha)			
sub-plot	Duration for coverage intensity		
	dense	medium	sparse
A	13	8	7
B	14	11	12

Table 2. Comparison of data acquisition duration at research plots.

3.2 Artificial objects

RMSE acquired the following values when evaluating the positional accuracy of objects – cubes: at the plot 1 the total RMSE acquired the highest value on the sub-plot F for the second type of trajectory (medium) 0.125 m, on the contrary the lowest value was also recorded on the sub-plot F for the first

type trajectory (dense) 0.105 m. At the plot 2, the differences in RMSE between sub-plots are evident. The values of the total RMSE in the first sub-plot A acquire the values 0.068, 0.090 and 0.085 m, while in the sub-plot B the values are several times higher - 0.798, 0.852 and 0.832 m. In the case of plot 2, RMSE grows directly moderately with higher area coverage.

3.3 SLAM trajectory

When evaluating the positional accuracy of HMLS trajectories, 133 differences between points on trajectory and reference points at plot 1 and 113 differences at plot 2 out of a total of 12 measurements were processed.

The RMSE in evaluating the positional accuracy of the HMLS trajectory acquired the following values: the total RMSE acquired the highest value at site 1 in sub-plot F in the first type of data collection 0.432 m. It acquires the lowest value at the studied locality at the sub-plot G at the third type of data collection 0.299 m.

At the plot 2, RMSE acquires the highest value in sub-plot B at the second type of data collection 0.566 m. The lowest RMSE value can be seen at the partial area A at the first type of data collection 0.399 m. It is evident that a very high value of the partial RMSE in the Z direction, which is in all cases several times higher than the values in the directions of the other two axes, has a significant effect on the RMSE results.

3.4 IMU trajectory

The evaluation of the positional accuracy of the INS trajectory brings the following outcomes: At the plot 1, the success rate was significantly worse than in the case of the plot 2. Out of six trials at the plot 1, the calculation was completely successful in only two cases and in the remaining cases the processing software reported a data error that does not allow further processing. In the case of plot 2, the results were more favourable, out of six attempts, we encountered a calculation failure in only one case. A total of seven trajectories were successfully calculated from twelve collection tests at the two research plots.

At the plot 1, 60 differences between points on trajectory and reference points, and 132 differences at plot 2 out of a total of 7 measurements were processed. RMSE obtained the following values when evaluating the positional accuracy considering the X and Y axes: the total RMSE gained the highest value at plot 1 in sub-plot G at the second type of data collection 2.83 m. It acquires the lowest value in the given locality on the partial area F at the first type of data collection 0.927 m. At plot 2, RMSE acquires the highest value in sub-plot B at the third type of data collection 15,729 m. It acquires the lowest value in the given locality in the sub-plot A at the first type of data collection 9.925 m.

3.5 Natural objects

The primary way to evaluate the positional accuracy of the used devices can be considered the evaluations of the accuracy of the reference point signals described above. In the following section, the evaluation of the positional accuracy of the derived positions of the trees extracted from the point cloud created by HMLS with SLAM continues.

During the evaluation, 217 differences between derived and reference tree position at the plot 1 and 301 differences at the plot 2 out of a total of 12 measurements were processed. The RMSE in the evaluation of the positional accuracy of the objects took the following values: at the plot 1 the total RMSE acquired the highest value on the sub-plot F at the third trajectory type

0.117 m, on the contrary the lowest value was recorded on the partial area G at the first type of trajectory 0.137 m. At the plot 2, the differences in RMSE between the sub-plots are not as evident as was the case when evaluating the positional accuracy of artificial objects - cubes. The total RMSE gained the highest value in the sub-plot and in the first type of trajectory 0.501 m, on the contrary, the lowest value was also recorded in the sub-plot A in the third type of trajectory 0.232 m. At the plot 2, the total RMSE values are in each case higher by more than 10 centimetres, which we attribute to the impact of the stand on data collection.

4. DISCUSSION

We tested hand-held mobile laser scanner GeoSLAM ZEB Horizon and inertial navigation system SPAN NovAtel inside a forest environment for accurate positioning. These devices differ mainly in the way they access location data. Although the INS provide position data immediately, without additional devices the positional deviations appear too high. In contrast, HMLS requires postprocessing, the quality of positional data for both investigated types of objects (natural and artificial) are many times higher. One of the assumptions was the claim that by thoughtful data collection it is possible to refine the estimation of the location of objects to the level which complies with the accuracy standards. We can clearly state that the data from the used HMLS meet the assumptions in all directions. In this work we achieved an average RMSE determination of the position of derived artificial objects at the level of 0.26 m in 2D, and average RMSE accuracy of the device trajectory 0.403 m in 3D.

With the INS device an average size of the horizontal position deviation (2D) in real time of 2.3 ft (0.70 m) and after postprocessing processing of 1.4 ft (0.42 m) compared to the reference data from the total station was achieved (Reutebuch et al., 2003). Also with the NovAtel device, publishes results on solving the position of the vehicle's trajectory points in a forest environment at the sub-meter level (Soloviev et al., 2012).The fusion integrating the laser sensor and GPS technology in the off-line generation of the stand map achieved an accuracy of determination with an error of 0.55 m (in 2D) measured at sample points (Aguiar et al., 2020; Rossmann et al., 2009). In this case, we see similarities in the design of the experiment and the technology used, where accuracy is evaluated at reference points and we can say that using GNSS technology in integration with IMU, we achieved in 2D an average RMSE of 9.93 m, in the case of SLAM equipment and position of artificial objects to 0.13 m, for natural objects up to 0.09 m.

Comparing the results with the work of (Hussein et al., 2015) on autonomous navigation in the forest operating based on scanning scans with an average error in the position of the robot of less than 2 m, the results of our research are not shown in the best light. It should be noted that the mentioned works date back several years, so there is a presumption of the progress of the compared technological procedures and increasing the accuracy of positioning in the forest. Essential in all the mentioned works the carrier on which the device is placed, because the motorized devices are not capable of such sudden changes of movement as the operator during walking. We therefore assume that this factor has a significant impact on the quality of the results. It is also important to note that data from site 2 - young, denser stand - have a significant share in the final average RMSE. At the same time, those are disproportionate to the data from locality 1 - older stand, the data from only two collections were successfully evaluated, while at site 1 were five successful collections. For information, we state that after data distribution,

the average RMSE at site 1 is 1.66 m, while at site 2 it is 9.16 m.

When comparing our results of GNSS integration with IMU in 2D, we lag the work, which also works with the fusion of GNSS and INS and achieves a positional accuracy of 0.13 m in mapping (Qian et al., 2017). The authors used GNSS and INS data to correct SLAM device data, and thus it is more complex forest mapping solution than INS backpack SPAN (GNSS + INS) provides separately. From recent work, author described a point cloud coupling approach based on Delaunay triangulation in autonomous harvester navigation, where 2D localization accuracy result was at a 12 cm error level on the tested sequence in real time at speeds up to 0.5 m/s (Li et al., 2020). However, as in the case of the previous work (Qian et al., 2017) GNSS and INS are used in integration with another system, which allows both wider usability and more accurate results. Authors discuss about combining laser odometry with IMU when measuring a stem diameter with an error of 7.1 m at a length of 260 m (Hyyti and Visala, 2013). This value is similar to our results when evaluating the INS backpack trajectory in 2D, where we achieved an average RMSE of 9.93 m, the similarity of the work we see in both cases is not an advanced fusion of modern sensors and different real-time positioning methods, as we are talking about odometry in combination with IMU. Recent works maps for example an unstructured environment in the form of a snowy forest using a fusion of IMU, GPS, LIDAR, and camera sensors where the error in trajectory shift at the level of 0.36 m (Chahine et al., 2021). It is obvious that this result is much better in 3D (SPAN GNSS and INS - average RMSE 9.93 m), but again it is important to emphasize that the integration of sensors refines the results significantly.

Based on this work and the previously mentioned work, we state that integration is more than desirable if we consider using the GNSS + INS assembly for space mapping or positioning. It is important to consider the circumstances and determine the exact requirements for specific research tasks, as well as to consider the costs of procuring equipment and possible substitution for other options which are more advantageous.

To clearly demonstrate the potential of HMLS with SLAM technology, a comparison with other options is needed in terms of data collection efficiency in a specific environment. The authors use different methods and procedures, for comparison it is appropriate to calculate the area (m^2) versus time (min.) per operator. Some authors performed relatively long-term data acquisition, which could be caused by nature of research location, e.g., a value of 20 m^2/min. per operator (Ryding et al., 2015) or 30 m^2/min. per operator were achieved by (Chen et al., 2019). Both studies were held within forest stand in extravillain. On the other hand, some works demonstrate much more effectivity during data collection. Study carried out in an urban park with effectiveness of 107.53 m^2/min. per operator (Cabo et al., 2018). Even more outstanding results with a value of 123.81 m^2/min. per operator at a coastal cliff were published in (James and Quinton, 2014). In our study, average data acquisition time for locality 1 (133/trees/ha) was 50.08 m^2/min. per operator and 61.51 m^2/min. per operator at the locality 2 (344trees/ha). These outcomes are comparable to similar studies located at forest stands mentioned before. Our results underline the fact that tree density on location where the research is carried out has an impact on duration of data acquisition.

When assessing the work dealing with SLAM technology in specific forest conditions, our results are comparable with results achieved in 2D when deriving the amount of biomass with a maximum error <32 cm, with the technology of combining scans based on SLAM (Tang et al., 2015). With the

Google Tango was reached RMSE over one meter for the Spiral pattern and 0.20 m for the Sun pattern of data collection (Tomaštík et al., 2017).

Comparing SLAM HMLS with TLS in deriving DHB and tree position shows that the position of the trunk reached RMSE at 1.5 cm and 2.1 cm (Ryding et al., 2015) . The trend of using TLS results as reference data is evident mainly in works focused on derivation of DBH, or other characteristics of individual trees or stands e.g., (Hyyppä et al., 2020c) in work about derivation of stem curves and stem volume from point cloud acquired by carried MLS. The positional RMSE 20 cm (HMLS) and 62 cm BPLS (backpack laser scanner) were achieved by (Oveland et al., 2017). Later, TLS, HMLS and a BPLS were compared with GNSS and total station referred dataset and reached positional RMSE 82 cm (TLS), 20 cm (HMLS) and 62 cm (BPLS), and also 6.2 cm (TLS), 3.1 cm (HMLS) and 2.2 cm (BPLS) RMSE of DBH (Oveland et al., 2018).

However, when evaluating the position of objects in real space, we consider it as necessary to operate with reference data, which are made according to certain standards for a specific type of task. When researching the use of SLAM technology in a forest environment achieves a mean tree positioning error of 4.76 cm with automated 3D mapping in forests with a tailor-made mobile platform (Pierzchała et al., 2018). Our results in evaluating the positional accuracy of objects are RMSE 29 cm for unnatural (cubes) and RMSE 23 cm for natural objects (trees). In research focused on real-time appearance mapping of trees for large-scale forest inventory, RMSE reached more than 30 cm in the x, y and z axes (Fan et al., 2020). This is followed by our results and the average RMSE with a height of 40 cm, which we achieved when evaluating the accuracy of determining the position of the SLAM trajectory in the forest environment. The exploration concludes with the work focused on navigation and mapping in forest environments using sparse point clouds (comparison of two methods for autonomous harvester navigation - sparse sSLAM and standard LeGO-LOAM - dense SLAM method) with an average positioning error against GNSS of approximately 50 cm per 100 m of the path (Nevalainen et al., 2020).

SLAM technology has potential to be widely used in forestry practice in many tasks. Based on previous research, we assume the negative impact of the high range of the device and the dense coverage of the area in an environment where the objects are very similar to each other (forest environment - trees). These enter the SLAM algorithm just at the limit of the range of the device, and due to the mentioned properties, they can be interchanged, as their morphological structure is similar, and the terrain conditions are never ideal. Therefore, we proposed at the beginning of the experiment to determine the maximum distance from which the collected points will enter the SLAM algorithm and use this value when exporting data, which will also ensure more acceptable hardware computing capacity, as the data will be smaller. The above information forms the basis for planning further experiments.

The analysis of variance showed that the data do not show a significant difference in the case of evaluating the positional accuracy of artificial objects at defined inputs (stand age and density of the research area). We consider this result to be crucial and its confirmation should be verified by identical experiments on stands which will be even more different in the stand characteristics than the ones we have selected for the needs of this topic.

5. CONCLUSION

The main goal of the presented work was to evaluate the positional accuracy of objects recorded by alternative approaches in the field of obtaining positional data in the forest environment. Following this, assess the suitability of the use of individual technologies in relation to the standards of positioning accuracy, as well as a possible increase in the effectiveness of mapping work in the forest environment. The high potential of the devices and the application of data collection methods into forest practice were pointed out in the results of this study. In this study, horizontal position of artificial objects (cubes) was evaluated with the average RMSE of 0.26 m and the average positional RMSE of the derived natural object (trees) was 0.09 m, both extracted from HMLS with SLAM achieved. The horizontal positional accuracy of trajectories with RMSE of 9.93 m (INS) and 0.40 m (SLAM) was accomplished.

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REFERENCES

Aguiar, A.S., Santos, F.N. Dos, Cunha, J.B., Sobreira, H., Sousa, A.J., 2020. Localization and mapping for robots in agriculture and forestry: A survey. Robotics 9, 1–23. https://doi.org/10.3390/robotics9040097

Ali, I., Durmush, A., Suominen, O., Yli-Hietanen, J., Peltonen, S., Collin, J., Gotchev, A., 2020. FinnForest dataset: A forest landscape for visual SLAM. Rob. Auton. Syst. 132, 103610. https://doi.org/10.1016/j.robot.2020.103610

Bakuła, M., Oszczak, S., Pelc-Mieczkowska, R., 2009. Performance of RTK positioning in forest conditions: Case study. J. Surv. Eng. 135, 125–130.

Bakuła, M., Przestrzelski, P., Kaźmierczak, R., 2015. Reliable Technology of Centimeter GPS/GLONASS Surveying in Forest Environments. IEEE Trans. Geosci. Remote Sens. 53, 1029–1038. https://doi.org/10.1109/TGRS.2014.2332372

Bonnor, N., 2014. Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems – Second EditionPaul D. Groves Artech House, 2013, 776 pp ISBN-13: 978-1-60807-005-3. J. Navig. 67, 191–192. https://doi.org/10.1017/S0373463313000672

Cabo, C., Ordóñez, C., López-Sánchez, C.A., Armesto, J., 2018. Automatic dendrometry: Tree detection, tree height and diameter estimation using terrestrial laser scanning. Int. J. Appl. Earth Obs. Geoinf. 69, 164–174. https://doi.org/10.1016/j.jag.2018.01.011

Chahine, G., Vaidis, M., Pomerleau, F., Pradalier, C.C., 2021. Mapping in unstructured natural environment: a sensor fusion framework for wearable sensor suites. SN Appl. Sci. 3. https://doi.org/10.1007/s42452-021-04555-y

Chen, S., Liu, H., Feng, Z., Shen, C., Chen, P., 2019. Applicability of personal laser scanning in forestry inventory. PLoS One 14, 1–22. https://doi.org/10.1371/journal.pone.0211392

Chudá, J., Hunčaga, M., Tuček, J., Mokroš, M., 2020. THE HANDHELD MOBILE LASER SCANNERS AS A TOOL FOR ACCURATE POSITIONING UNDER FOREST CANOPY. ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLIII-B1-2, 211–218. https://doi.org/10.5194/isprs-archives-XLIII-B1-2020-211-2020

Danskin, S., Bettinger, P., Jordan, T., 2009. Multipath Mitigation under Forest Canopies: A Choke Ring Antenna Solution. For. Sci. 55, 109–116. https://doi.org/10.1093/forestscience/55.2.109

Danson, F., Disney, M., Gaulton, R., Schaaf, C., Strahler, A., 2018. The terrestrial laser scanning revolution in forest ecology. Interface Focus 8, 20180001. https://doi.org/10.1098/rsfs.2018.0001

Fan, Y., Feng, Z., Shen, C., Khan, T.U., Mannan, A., Gao, X., Chen, P., Saeed, S., 2020. A trunk-based SLAM backend for smartphones with online SLAM in large-scale forest inventories. ISPRS J. Photogramm. Remote Sens. 162, 41–49. https://doi.org/10.1016/j.isprsjprs.2020.02.006

Gillet, J., Scherzinger, B.M., Lithopoulos, E., 2000. Inertial / GPS System for Seismic Survey.

Hide, C., Moore, T., Smith, M., 2003. Adaptive Kalman Filtering for Low-cost INS/GPS. J. Navig. 56, 143–152. https://doi.org/10.1017/S0373463302002151

Holopainen, M., Kankare, V., Vastaranta, M., Liang, X., Lin, Y., Vaaja, M., Yu, X., Hyyppä, J., Hyyppä, H., Kaartinen, H., Kukko, A., Tanhuanpää, T., Alho, P., 2013. Tree mapping using airborne, terrestrial and mobile laser scanning – A case study in a heterogeneous urban forest. Urban For. Urban Green. 12, 546–553. https://doi.org/https://doi.org/10.1016/j.ufug.2013.06.002

Hunčaga, M., Chudá, J., Tomaštík, J., Slámová, M., Koreň, M., Chudý, F., 2020. The comparison of stem curve accuracy determined from point clouds acquired by different terrestrial remote sensing methods. Remote Sens. 12. https://doi.org/10.3390/RS12172739

Hussein, M., Renner, M., Iagnemma, K., 2015. Global localization of autonomous robots in forest environments. Photogramm. Eng. Remote Sensing 81, 839–846. https://doi.org/10.14358/PERS.81.11.839

Hyyppä, E., Hyyppä, J., Hakala, T., Kukko, A., Wulder, M.A., White, J.C., Pyörälä, J., Yu, X., Wang, Y., Virtanen, J.P., Pohjavirta, O., Liang, X., Holopainen, M., Kaartinen, H., 2020a. Under-canopy UAV laser scanning for accurate forest field measurements. ISPRS J. Photogramm. Remote Sens. 164, 41–60. https://doi.org/10.1016/j.isprsjprs.2020.03.021

Hyyppä, E., Kukko, A., Kaijaluoto, R., White, J.C., Wulder, M.A., Pyörälä, J., Liang, X., Yu, X., Wang, Y., Kaartinen, H., Virtanen, J.-P., Hyyppä, J., 2020b. Accurate derivation of stem curve and volume using backpack mobile laser scanning. ISPRS J. Photogramm. Remote Sens. 161, 246–262. https://doi.org/10.1016/j.isprsjprs.2020.01.018

Hyyppä, E., Yu, X., Kaartinen, H., Hakala, T., Kukko, A., Vastaranta, M., Hyyppä, J., 2020c. Comparison of backpack, handheld, under-canopy UAV, and above-canopy UAV laser scanning for field reference data collection in boreal forests. Remote Sens. 12, 1–31. https://doi.org/10.3390/rs12203327

Hyyti, H., Visala, A., 2013. Feature Based Modeling and Mapping of Tree Trunks and Natural Terrain Using 3D Laser Scanner Measurement System. IFAC Proc. Vol. 46, 248–255. https://doi.org/https://doi.org/10.3182/20130626-3-AU-2035.00065

James, M.R., Quinton, J.N., 2014. Ultra-rapid topographic

surveying for complexenvironments: the hand-held mobile laser scanner(HMLS). Earth Surf. Process. Landforms 39, 138–142. https://doi.org/10.1002/esp.3489

Kaartinen, H., Hyyppä, J., Vastaranta, M., Kukko, A., Jaakkola, A., Yu, X., Pyörälä, J., Liang, X., Liu, J., Wang, Y., Kaijaluoto, R., Melkas, T., Holopainen, M., Hyyppä, H., 2015. Accuracy of kinematic positioning using global satellite navigation systems under forest canopies. Forests 6, 3218–3236. https://doi.org/10.3390/f6093218

Keefe, R.F., Wempe, A.M., Becker, R.M., Zimbelman, E.G., Nagler, E.S., Gilbert, S.L., Caudill, C.C., 2019. Positioning methods and the use of location and activity data in forests. Forests 10. https://doi.org/10.3390/f10050458

Koreň, M., 2019. DendroCloud User Guide: Version1.49.

Lee, J.Y., Kim, H.S., Choi, K.H., Lim, J., Kang, S.J., Chun, S., Lee, H.K., 2013. Design of adaptive filtering algorithm for relative navigation. Lect. Notes Eng. Comput. Sci. 2, 892–896.

Li, Q., Nevalainen, P., Peña Queralta, J., Heikkonen, J., Westerlund, T., 2020. Localization in Unstructured Environments: Towards Autonomous Robots in Forests with Delaunay Triangulation. Remote Sens. . https://doi.org/10.3390/rs12111870

Liang, X., Hyyppä, J., Kaartinen, H., Lehtomäki, M., Pyörälä, J., Yu, X., Pfeifer, N., Brolly, G., Francesco, P., Hackenberg, J., Huang, H., Jo, H.W., Katoh, M., Liu, L., Mokroš, M., Morel, J., Olofsson, K., Poveda-Lopez, J., Trochta, J., Wang, D., Wang, J., Xi, Z., Yang, B., Zheng, G., Kankare, V., Vastaranta, M., Wang, Y., 2019. International benchmarking of terrestrial laser scanning approaches for forest inventories. Off. Publ. - EuroSDR 2019, 1–53. https://doi.org/10.1016/j.isprsjprs.2016.01.006

Liang, X, Hyyppä, J., Kukko, A., Kaartinen, H., Jaakkola, A., Yu, X., 2014. The Use of a Mobile Laser Scanning System for Mapping Large Forest Plots. IEEE Geosci. Remote Sens. Lett. 11, 1504–1508. https://doi.org/10.1109/LGRS.2013.2297418

Liang, X., Kankare, V., Hyyppä, J., Wang, Y., Kukko, A., Haggrén, H., Yu, X., Kaartinen, H., Jaakkola, A., Guan, F., Holopainen, M., Vastaranta, M., 2016. Terrestrial laser scanning in forest inventories. ISPRS J. Photogramm. Remote Sens. 115, 63–77. https://doi.org/10.1016/J.ISPRSJPRS.2016.01.006

Liang, Xinlian, Kukko, A., Kaartinen, H., Hyyppä, J., Yu, X., Jaakkola, A., Wang, Y., 2014. Possibilities of a Personal Laser Scanning System for Forest Mapping and Ecosystem Services. Sensors . https://doi.org/10.3390/s140101228

Liang, X., Wang, Y., Jaakkola, A., Kukko, A., Kaartinen, H., Hyyppä, J., Honkavaara, E., Liu, J., 2015. Forest data collection using terrestrial image-based point clouds from a handheld camera compared to terrestrial and personal laser scanning. IEEE Trans. Geosci. Remote Sens. 53, 5117–5132. https://doi.org/10.1109/TGRS.2015.2417316

Nevalainen, P., Li, Q., Melkas, T., Riekki, K., Westerlund, T., Heikkonen, J., 2020. Navigation and mapping in forest environment using sparse point clouds. Remote Sens. 12, 1–19. https://doi.org/10.3390/rs12244088

Oveland, I., Hauglin, M., Giannetti, F., Schipper Kjørsvik, N., Gobakken, T., 2018. Comparing Three Different Ground Based Laser Scanning Methods for Tree Stem Detection. Remote Sens. 10. https://doi.org/10.3390/rs10040538

Oveland, I., Hauglin, M., Gobakken, T., Næsset, E., Maalen-Johansen, I., 2017. Automatic Estimation of Tree Position and Stem Diameter Using a Moving Terrestrial Laser Scanner. Remote Sens. 9. https://doi.org/10.3390/rs9040350

Perugia, B. Del, Giannetti, F., Chirici, G., Travaglini, D., 2019. Influence of scan density on the estimation of single-tree attributes by hand-held mobile laser scanning. Forests 10, 1–13. https://doi.org/10.3390/f10030277

Pierzchała, M., Giguère, P., Astrup, R., 2018. Mapping forests using an unmanned ground vehicle with 3D LiDAR and graph-SLAM. Comput. Electron. Agric. 145, 217–225. https://doi.org/https://doi.org/10.1016/j.compag.2017.12.034

Qian, C., Liu, H., Tang, J., Chen, Y., Kaartinen, H., Kukko, A., Zhu, L., Liang, X., Chen, L., Hyyppä, J., 2017. An integrated GNSS/INS/LiDAR-SLAM positioning method for highly accurate forest stem mapping. Remote Sens. 9, 1–16. https://doi.org/10.3390/rs9010003

Reutebuch, S., Carson, W., Ahmed, K., 2003. A Test of the Applanix POS LS Inertial Positioning System for the Collection of Terrestrial Coordinates under a Heavy Forest Canopy.

Rossmann, J., Krahwinkler, P., Schiette, C., 2009. Navigation of mobile robots in natural environments: Using sensor fusion in forestry. IMETI 2009 - 2nd Int. Multi-Conference Eng. Technol. Innov. Proc. 3, 5–9.

Ryding, J., Williams, E., Smith, M.J., Eichhorn, M.P., 2015. Assessing handheld mobile laser scanners for forest surveys. Remote Sens. 7, 1095–1111. https://doi.org/10.3390/rs70101095

Sedmák, R., 2009. Modelovanie rastu bukových stromov a porastov.

Šmelko, Š., 2015. Dendrometria. Technical university in Zvolen, Zvolen.

Soloviev, A., Toth, C., Grejner-Brzezinska, D., 2012. Performance of deeply integrated GPS/INS in dense forestry areas. J. Appl. Geod. 6, 3–13. https://doi.org/doi:10.1515/jag-2011-0005

Tachiki, Y., Yoshimura, T., Hasegawa, H., Mita, T., Sakai, T., Nakamura, F., 2005. Effects of polyline simplification of dynamic GPS data under forest canopy on area and perimeter estimations. J. For. Res. 10, 419–427.

Tang, J., Chen, Y., Kukko, A., Kaartinen, H., Jaakkola, A., Khoramshahi, E., Hakala, T., Hyyppä, J., Holopainen, M., Hyyppä, H., 2015. SLAM-aided stem mapping for forest inventory with small-footprint mobile LiDAR. Forests 6, 4588–4606. https://doi.org/10.3390/f6124390

Tomaštík, J., Saloň, Š., Tunák, D., Chudý, F., Kardoš, M., 2017. Tango in forests – An initial experience of the use of the new Google technology in connection with forest inventory tasks. Comput. Electron. Agric. 141, 109–117. https://doi.org/10.1016/j.compag.2017.07.015

Wang, J.-G., Gopaul, S.N., Guo, J., 2010. Adaptive Kalman Filtering Based on Posteriori Variance-Covariance Components Estimation. Proc. CPGPS 2010 Tech. Forum 1–11.

Welch, G., Bishop, G., 2006. An Introduction to the Kalman Filter. In Pract. 7, 1–16. https://doi.org/10.1.1.117.6808

Yang, Y., Monserud, R., Huang, S., 2004. An evaluation of diagnostic test and their roles in validating forest biometric models. Can. J. For. Res. Can. Rech. For. - CAN J For. RES 34, 619–629. https://doi.org/10.1139/x03-230