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Terrestrial laser scanning in forest inventories

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ABSTRACT

Decision making on forest resources relies on the precise information that is collected using inventory. There are many different kinds of forest inventory techniques that can be applied depending on the goal, scale, resources and the required accuracy. Most of the forest inventories are based on field sample. Therefore, the accuracy of the forest inventories depends on the quality and quantity of the field sample. Conventionally, field sample has been measured using simple tools. When map is required, remote sensing materials are needed. Terrestrial laser scanning (TLS) provides a measurement technique that can acquire millimeter-level of detail from the surrounding area, which allows rapid, automatic and periodical estimates of many important forest inventory attributes. It is expected that TLS will be operationally used in forest inventories as soon as the appropriate software becomes available, best practices become known and general knowledge of these findings becomes more wide spread. Meanwhile, mobile laser scanning, personal laser scanning, and image-based point clouds became capable of capturing similar terrestrial point cloud data as TLS. This paper reviews the advances of applying TLS in forest inventories, discusses its properties with reference to other related techniques and discusses the future prospects of this technique.

1. Introduction

Forest resource information is gathered for planning and managing of various ecosystem services at various user-levels, from worldwide political decision making to operational forest management, and at various scales, from countrywide assessments to stand-level measurements. At the national and global scale, the main goal of the inventory is to collect information on forested area such as biomass, stem volume, biodiversity and changes in these attributes. At the regional and forest holding level, it is important to also collect information from timber harvesting potential and from forest operations. To meet the goals of the inventory, there are many different kinds of techniques depending on the available resources and the required accuracy. Most of the forest inventories are based on field samples. Field samples can be used to calculate means and totals over area of interest or to aid remote-sensing-based forest mapping. Therefore, the accuracy of the forest inventories depends on the quality and quantity of the field sample.

Forest sample plots are typically a small forest area, e.g., circular in shape with a radius varying from 4 m to 15 m. Tree information is usually collected in forest field inventories through tree-by-tree measurements. The main information consists of tree attributes such as species, diameter at breast height (DBH) and tree height. In the current inventory practices, tree-by-tree measures are mostly aggregated to plot-level means and totals. For example, the basal area per hectare is calculated from tree-level DBH measurements and the aggregation is based on the sample plot size. Conventionally, field sample has been measured using simple tools, such as calipers and clinometers, and the advancement of forest field inventories has been slow in the past. The situation experienced a dramatic change in the last two decades because of the introduction of terrestrial laser scanning (TLS), also known as ground-based Light Detection and Ranging (LiDAR).

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0924-2716/

Three fundamental aspects shape the adaptation of any new technique in measuring tree-by-tree information in sample plots in forest inventories: (1) The cost of the data acquisition and data interpretation should be affordable. The costs originate mainly from the equipment, time consumption of data acquisition (e.g., field work) and post-processing of the data. (2) The accuracy of the tree attribute estimation should be at the same level or surpass the conventional technique, or the gained added value from the new technique should be significant. (3) The technique should focus primarily on tree attributes that are important for forest management decision-making at varying scales and time horizons. These three factors interact intimately. The minimized cost often leads to a smaller amount of tree attributes measured. The higher accuracy often requires better data and the measurement costs are on the increase consequently.

TLS automatically measures the surrounding three-dimensional (3D) space using millions to billions 3D points. The major advantage of using TLS in forest inventories lies in its capability to document the forest rapidly, automatically and in millimeter-level detail. The first commercial TLS system was built by Cyra Technologies (acquired by Leica in 2001) in 1998, and early works related to tree attribute estimation in forest inventories were reported around 2000 (Erikson and Karin, 2003; Lovell et al., 2003; Hopkinson et al., 2004; Parker et al., 2004; Thies et al., 2004; Henning and Radtke, 2006a). The initial motivation for using TLS in forest inventories was to improve the work efficiency in the sample plots, i.e., replacing manually measured tree attributes with those retrieved automatically from TLS data. Therefore, TLS has been used in collecting basic tree attributes in sample plots, such as DBH and tree position (Bienert et al., 2006; Maas et al., 2008; Vastaranta et al., 2009; Murphy et al., 2010).

More recently, TLS has been shown to be capable of determining high-quality tree attributes that are important but are not directly measurable in conventional forest inventories, such as stem volume and biomass components (total, stem and branches), with accuracy levels that are similar to the best national allometric models, such as in Yu et al. (2013), Kankare et al. (2013), Liang et al. (2014), Astrup et al. (2014) and Newnham et al. (2015). TLS data also permit time series analyses because the entire plot can be documented consecutively over time, such as in Liang et al. (2012a) and Srinivasan et al. (2014). With these latest research results, TLS has shown the possibility to improve the quality and quantity of the reference data collected in the forest inventories.

It is worth to note that TLS is also a popular tool in forest ecology. The use of TLS has been intensively studied, e.g., for the estimation of leaf area index (Hosoi and Omasa, 2006; Strahler et al., 2008; Jupp et al., 2009; Huang and Pretzsch, 2010; Hopkinson et al., 2013; Zheng et al., 2013), gap fraction (Danson et al., 2007; Seidel et al., 2012; Zhao et al., 2012; Cifuentes et al., 2014), canopy radiation (Van der Zande et al., 2011; van Leeuwen et al., 2013), crown structure (Moorthy et al., 2011; Bayer et al., 2013) and leaf area distributions (Béland et al., 2011). TLS studies aimed at forest ecology and forest inventories share certain common interests. For example, the basic tree attributes, such as the tree species, tree height, DBH and biomass, are collected in both research areas. However, most tree attributes that are intensively used in forest ecology are not measured in forest inventories, and vice versa, such as the leaf area index and the stem curve.

This paper reviews the advances of using TLS in forest inventories since TLS became available, discusses its properties with reference to other similar and competing techniques and highlights its future prospects. Section 2 describes the TLS system, data and measurement principles. Section 3 specifies methods and applications of TLS in forest inventories. Section 4 reviews studies reported in literatures. Section 5 reviews contemporary technologies that produce terrestrial point cloud and evaluates their advantages and disadvantages. Section 6 discusses the prospects of using TLS in forest inventories. The conclusions are summarized in Section 7.

2. TLS system, data and measurement principles

Laser measurements have been utilized in standard surveying application instruments for the past decades to measure object geometry. A total station, for instance, is used by a field surveyor to measure individual feature points with a high degree of accuracy. In the late 1990s, this manual and specific measuring mechanism was further developed into an automated and non-specific documentation of the entire surrounding 3D space by dense 3D measurements, i.e., terrestrial laser scanning.

2.1. TLS system

TLS is a laser-based instrument that measures its surroundings using LiDAR for range measurement and precise angular measurements through the optical beam deflection mechanism to derive 3D point observations from the object surfaces.

Two main techniques are used for the range measurement in current laser scanning systems: phase shift (PS) and time-of-flight (ToF) methods. PS ranging makes use of continuous laser illumination and amplitude modulation of the beam to discern the range at high frequency. ToF utilizes precise timing for determining the range from the pulse time of flight and the speed of light. In ToF, for each emitted laser pulse, the backscattered part of the laser signal may be recorded at the receiver as just one return exceeding the detection threshold or several returns (e.g., single, first, last and intermediate). A multi-return system typically produces a much denser point cloud in comparison with a single-return system, especially in a vegetated area, because the backscattered signals may arise from targets inside of and/or behind vegetation. Besides discrete returns, a backscattered laser signal may be consecutively digitized at the receiver, which gives a waveform data. Waveform includes data representing interactions between a laser pulse and targets in the laser beam direction, which can potentially be used to retrieve additional information with respect to discrete returns.

The scanning mechanisms enable TLS to capture very dense (e.g., currently one million points per second) measurements in a short period of time. In a typical TLS instrument, the scanner measures the surrounding environment stepwise using a fast vertical mirror rotation and a slower horizontal instrument rotation, as shown in Fig. 1. In the vertical direction, the laser beam starts, for example, from the scanner zenith and rotates to the lowest scanning position below the horizontal plane of the instrument. Then, the laser beam continues to the scanner zenith on the other side of the instrument. In the horizontal direction, the scanner turns 180° and scans both sides of the instrument simultaneously.

More details on the scanning mechanism and measuring technique of TLS scanners can be found in Petrie and Toth (2009), Reshetyuk (2009) and Vosselman and Maas (2011).

TLS hardware has experienced a rapid improvement in the last two decades. The price, the size and the weight of the laser scanners decreased rapidly, with the constantly increased spatial resolution and the measurement speed. Currently, scanners provided by manufacturers such as FARO, Leica Geosystems, Trimble and Zöller & Fröhlich can measure up to one million points per second at the range of 100–300 m and the ranging precision is at a millimeter level. A digital camera is also commonly integrated to the scanner to provide color information (in red, green and blue) for the measured point cloud. The weight of a scanner can be just a few kilograms, e.g., 5.2 kg in the case of the Faro Focus^{3D}X 330. Manufacturers typically have several options for the hardware,

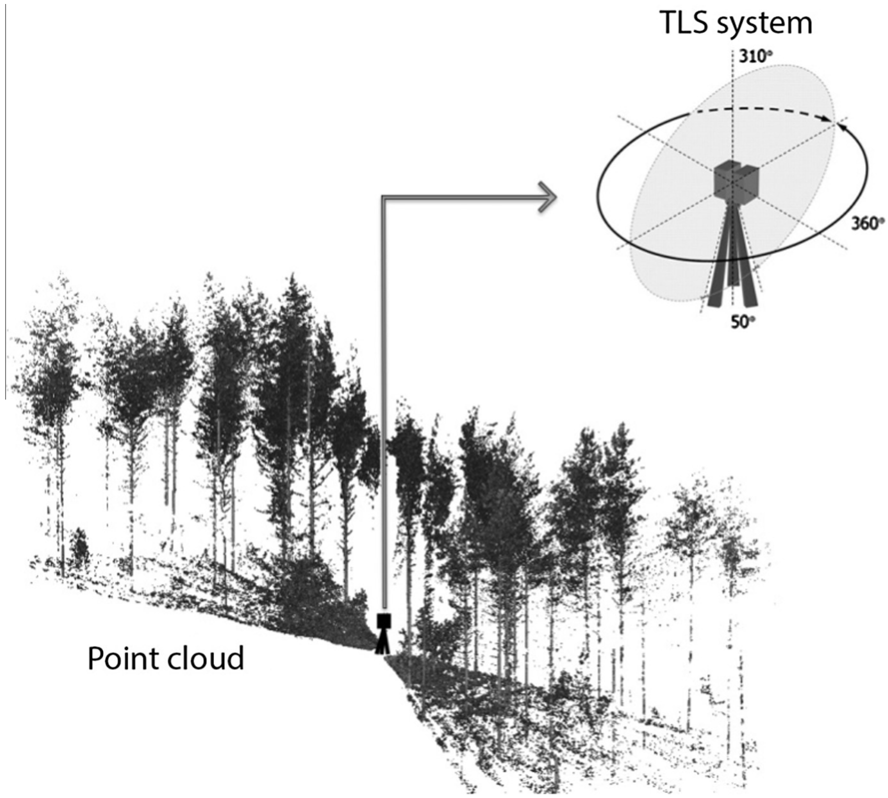

Fig. 1. The scanning mechanism of the TLS scanner and the point cloud data.

add-ons and software and they do not publish their pricelists. In general, the prices range from 30,000 to 80,000 euros.

New TLS systems are continuously being developed. Such advances may greatly benefit the processing chain. For example, the ground-point classification is improved in a multi-return system, as shown in Pirotti et al. (2013) and Calders et al. (2014), e.g., because a large part of the vegetation points can be removed by the return identifier. Dual-wavelength and hyperspectral TLS is currently being investigated (Tanaka, 2004; Hakala et al., 2012; Danson et al., 2014; Douglas et al., 2015; Puttonen et al., 2015). The use of multiple wavelengths makes it easier to classify targets, e.g., to separate leaf returns from the returns emanating from stems, branches and the ground. Reflectance from different wavelengths also enables studying other biochemistry features related to tree or leaves. The use of low-cost sensors to measure forest is also being investigated, e.g., in Eitel et al. (2013) and Kelbe et al. (2015).

2.2. System calibration

Systematic errors in laser scanners exist due to, e.g., imperfections in instrument manufacture and assemble. For example, rotation axes are assumed to be mutually orthogonal and to be intersected at a common point. In general these conditions are not met in real systems (Lichti and Skaloud, 2010). Random errors also accumulate. According to Soudarissanane et al. (2011), there are four main factors that influence the individual point quality in a point cloud, including (1) scanner mechanism, (2) atmospheric conditions and environment, (3) object properties and (4) scanning geometry.

Time-dependent changes associated with TLS and the TLS data also exist. Changes of environment conditions and wearing may introduce additional system errors. Instrument stability was tested by examining short- and long-term additional parameters in Lichti (2007). Ten self-calibration data sets were captured over a 13-month period. Only three of the additional parameters were found to be stable and significant differences were found over all other short- (hours and days) and long-term (over the course of 13 months) periods. For more system error sources and models, readers are refer to Thorsten (2007) and Lichti and Skaloud (2010).

TLS records intensities; however, currently, the backscattered energy is difficult to be linked to objects' properties. To improve the usability, the incidence angle effect on intensity data using TLS and laboratory instruments were investigated in Kukko et al. (2008). In a continuing effort (Kaasalainen et al., 2011), the range and incidence angle effects on the intensity measurement and radiometric calibration for different scanners were investigated to establish a correction scheme for both of these effects. In Lehner and Briese (2010), the incidence angle effect was incorporated in the radiometric calibration workflow.

In general, TLS measurements provide accurate enough data for most forest applications and the above mentioned systematic and random errors are less considered in practice. Higher impact on forest inventory accuracy originates from the methodologies and data acquisitions for forest attribute measurements.

2.3. TLS data

Basic TLS data include the range between the instrument and the object at each measuring position recorded by a laser rangefinder and two associated angles recorded by angular encoders. Additional attributes may be possibly associated with a point, e.g., the strength of the backscattered energy.

TLS data are commonly presented in a point cloud or matrix format. The point cloud consists of a large amount of x, y, z coordinates calculated from the original angle and range measurements. The advantage of the point cloud format is that it is recorded and provided by all TLS instruments. In other words, the point cloud data is the minimum intersection of different laser scanning hardware.

The matrix data are organized based on scanning mechanism. In a typical data matrix, the vertical scan line i is assigned as column i; the subsequent scan line $i+1$ then moves to the right with an increase in the horizontal angle. In each column, the vertical angle decreases from top to bottom, corresponding to the scanner zenith and feet. The entries in the matrix can be various direct or indirect observations, such as the intensity, range and distance. The advantage of the matrix format is that the 3D spatial distribution of the points in the object space is implicitly expressed by the two-dimensional (2D) spatial distribution of the pixels in the matrix. Therefore, data processing (e.g., segmentation) that uses spatial features in local 2D space functions similarly to that in the local 3D space, which requires less computation because the computational load typically increases exponentially with the dimension growth. The data matrix is, however, not always available because the row/column information may be deleted for noise removal and data compression reasons. It is possible to reconstruct a data matrix from the point cloud data if the scanner identifier exists.

The current TLS systems typically have a high spatial resolution. The range resolution is a few millimeters at several tenths of meters from the scanner, e.g., ±2 mm at 25 m. And the smallest angular sampling steps are less than 0.01° in both horizontal and vertical scanning directions. When using high angular resolution, the adjacent laser foot prints overlap at a close range. For example, given a beam diameter of 3 mm at the exit, a divergence of 0.22 mrad and an angular increase of 0.036° in both the horizontal and vertical directions, the adjacent footprints are fully separated at a distance of approximately 7 m from the scanning position. In field measurements, a high scanning resolution is typically used to record objects that are located far from the scanning position, e.g., tree tops and trees that are several tenths of meters away from the scanner. This leads to an inevitable high redundancy on objects close to the scanner. Therefore, it is important to carefully design the measurement geometry in the field according to the size, shape and structure of the forest sample plot, as well as the expected attributes from the TLS data. Data sampling is needed in certain cases, such as in Puttonen et al. (2013).

2.4. Data acquisition from sample plots

Three data acquisition approaches have been reported for TLS-based forest inventories: single-scan, multi-scan and multi-single-scan (MSS). The details of these three scanning scenarios are illustrated in Fig. 2.

In the single-scan mode, the laser scanner is placed at the plot center, creating only one full field-of-view (e.g., 360 × 310 degrees) scan, and the trees are mapped from the single-scan point cloud. In the multi-scan mode, several scans are made inside and outside of the plot to collect more detailed point clouds that represent the sample plot, and these scans are co-registered, e.g., by using artificial reference targets that are manually placed throughout the plot. The MSS approach includes the elements from both single- and multi-scan approaches. The scanning scenario is similar to that of the multi-scan approach. Several scans are made inside and outside of the plots; however, reference targets are not used. Instead of the data-level registration and merging individual datasets, different scans are registered at the feature level in the MSS approach. The MSS method first detects and maps the individual trees in the sample plot from each individual scan, and then merges the mapping results of the individual scans using the detected trees as reference objects to create an overall map of the sample plot. The fundamental rule used in the combination of the mapping results of several scans is to select an individual tree from the scan where it receives the best visibility among all the scans.

Among the three approaches, the single-scan approach has the simplest data acquisition setting and the fastest speed. A plot can be measured within 20 min: a full field-of-view scan typically takes 2–10 min, and it takes another 5–10 min to set up the scanner. The major problem is that, in most cases, only parts of the trees within the sample plot are scanned due to occlusion effects from the other objects (e.g., trees, branches, bushes, etc.) in the direction of the laser beams. The occlusion effect increases as the range from the scanner increases, depending on the forest structures. Studies have shown that up to 40% of all trees in the sample plot are not detectable from the plot center when using the single-scan approach (Brolly and Kiraly, 2009; Murphy et al., 2010; Lovell et al., 2011; Liang et al., 2012b; Astrup et al., 2014).

The multi-scan approach appears to be the most accurate technique for mapping forest sample plots. This approach has the potential to map all trees, depending on the plot structure (e.g., age, density and species), and has the potential to provide full coverage of the stem surface because the trees are scanned from several directions. However, the multi-scan approach requires more time in the field data acquisition and more efforts in the data processing, e.g., the manual or semi-automated registration of several scans. It usually takes approximately one hour to set up the scanners and reference targets and to scan a plot using 4–5 scans. Also,

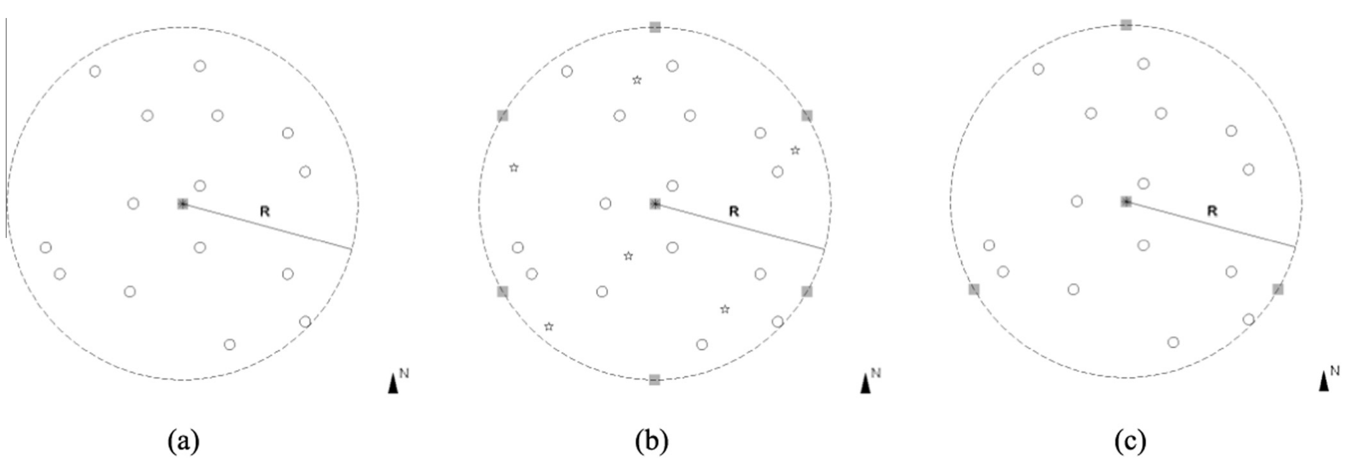

Fig. 2. The scanning scenarios of the single-scan (a), multi-scan (b) and multi-single-scan (c). The sample plot is a circular area with radius R. The plot center is marked with an asterisk. The positions of the trees are shown as solid circles. The reference targets are illustrated using stars, which are used only in the multi-scan TLS. The gray squares indicate the scanning locations.

tree movements, especially at the upper part of a tree, under different wind conditions cause problems for the multi-scan approach.

The MSS approach offers a compensation for the problem associated with the occlusion effects because objects occluded in one scan are likely be captured by other scans (Liang and Hyyppä, 2013). The workload for the MSS mapping scenario is lower in comparison with the multi-scan approach because reference targets and data registration are not used in MSS. In addition, MSS also minimizes the problem introduced by wind in the multi-scan approach where trees may start to sway, because only one scan is used for the estimation of tree attributes. The challenge of applying the MSS method is the matching of multiple data sets.

For certain research purposes (e.g., allometric model development), TLS data are acquired at a single tree level. When a single tree is considered as the only studying target, a tree is the equivalent of a plot. Therefore, the single- and multi-scan approaches are also applicable to the collect data from a single tree using TLS. In principle, the MSS approach can also be applied. MSS is less influenced by the wind effects, especially under moderate and heavy wind conditions. However, in allometric model development, MSS becomes less necessary because the measurement can be made in suitable environmental conditions (e.g., less windy) and the occlusion effects have been minimized by scanning a tree from several directions.

3. Methods and applications

The terrestrial point cloud rapidly became a favorable data source for tree modeling since the introduction of TLS because of the fast and automated data acquisition process as well as the 3D and detailed depiction of standing trees.

3.1. Tree modeling methods

Tree models are the basis for the tree attributes estimation. They are built at both the single-tree and plot levels. Two types of tree modeling share certain common components and at the same time require TLS data at different details.

3.1.1. Single tree modeling

Detailed tree models have great potential to be used in applications such as simulation, virtual reality and allometric model development. Single tree modeling has been studied for a long time in areas such as forestry, computer graphic and computer vision. Before TLS became available, data sources were typically photographs e.g., in Shlyakhter et al. (2001). The point cloud provides another data source to build a single tree model, such as in Cheng et al. (2007). In remote sensing applied to forestry, single tree modeling (Thies et al., 2004; Bucksch and Lindenbergh, 2008; Côté et al., 2009; Bucksch et al., 2010; Livny et al., 2010; Bremer et al., 2013; Raumonen et al., 2013; Delagrange et al., 2014; Hackenberg et al., 2014) and estimating single-tree attributes (Lefsky and McHale, 2008; Bucksch and Fleck, 2011; Fleck et al., 2011; Vonderach et al., 2012; Fernández-Sarría et al., 2013; Hosoi et al., 2013; Kankare et al., 2013; Hackenberg et al., 2015) have gained considerable popularity in recent years. In fact, single tree modeling has nowadays become a multi-discipline convergent point, where researches from computer graphic/vision, remote sensing, forest ecology and forestry meet.

In single tree modeling, only one tree exists in the data and the tree is recorded in the point cloud as comprehensively as possible in order to construct a detailed and completed model. This hypothesis is mostly confirmed in cases where trees completely (or mostly) stand separately, such as urban roadside trees (Lefsky and McHale, 2008; Vonderach et al., 2012), trees in a laboratory (Keightley and Bawden, 2010; Seidel et al., 2011), trees isolated in the field (Côté et al., 2011; Moorthy et al., 2011) and trees manually separated from the point cloud (Fleck et al., 2011). This hypothesis is often jointly confirmed in cases where a single tree is scanned from several directions, e.g., in Dassot et al. (2012), Schilling et al. (2012) and Delagrange et al. (2014). For example, every tree was scanned from three or four positions around it, and the scans were co-registered using five reference spheres in Dassot et al. (2012).

A single tree is typically modeled stepwise, e.g., from the tree bottom. A small piece of tree trunk or branch is reconstructed and the next piece is then modeled in the tree growth directions. Typically, trees are modeled by a skeleton, circle, cylinder or other geometric primitives.

3.1.2. Individual tree modeling and mapping at the plot level

The objective of the individual tree modeling at a plot level is to detect as many individual trees as possible in a plot and to extract various tree attributes (e.g., DBH, height, species, biomass and stem curve) from the 3D tree models. The final results for the plot-level individual tree modeling typically are a 2D plot map and 3D tree models of individual trees. Compared to the above described single-tree modeling, individual tree modeling at a plot-level differs mainly in data acquisition strategy and the level of details recorded in the data. In the single-tree modeling, one target tree, or its equivalent, is scanned using several scans from different directions to record the tree comprehensively, e.g., all branches. In the plot-level study, a forest sample plot is the target of TLS data collection and is scanned by one or several scans. Individual trees in the plot are typically occluded by other objects and the tree structure is usually incompletely recorded in the TLS data.

Individual tree detection is mandatory in the plot-level tree modeling. Three main method types have been reported for the detection of individual trees from TLS data at a plot level. They are 2D-layer searching, range-image clustering and point-cloud processing (Liang et al., 2012b).

In the 2D-layer searching technique, tree trunks are identified by point clustering or circle finding (Aschoff and Spiecker, 2004; Maas et al., 2008; Tansey et al., 2009; Lindberg et al., 2012), or by waveform analysis (Strahler et al., 2008; Yao et al., 2011), in a slice cut from the original point cloud. In order to construct the slice at a particular height, a Digital Terrain Model is required. An improvement is to repeat this procedure at several heights and circular objects in the several slices cut at different heights are marked as a detected tree.

In the range-image clustering method, pixels in the range image are grouped according to local properties, e.g. the distance or surface curvature (Haala et al., 2004; Forsman et al., 2012). This type of method requires modest computation because the neighborhood searching in 3D can be implemented in 2D. This method is, however, difficult to implement in the merged multi-scan data if the identifiers of the individual scans have been removed.

In the point-cloud processing method, individual points are studied for their, e.g., geometric properties, and semantic interpretations are made to identify the tree trunk (Liang et al., 2012b). This technique requires the largest amount of computation among three types of methods, but it can be applied in all kinds of point cloud data.

After the detection of individual trees, the tree modeling step shares similar concepts with the methods for the above mentioned single tree modeling. However, the individual tree modeling processes at a plot level need solutions to model trees where the point cloud data are less ideal because of, e.g., occlusion effects, the low point density and a high amount of noise at certain locations in the plot, even the multi-scan mode is used.

3.2. Level of details of 3D tree modeling

Tree models can be categorized into five different levels of details (LoD) considering the richness of the tree attributes and the cost of field data acquisition. Tree models at different LoDs are used in different applications.

LoD 1 is the most simple 3D tree model. A tree is represented by two basic tree parameters, i.e., DBH and tree height. In LoD 2, the tree position and 3D model of the main stem are added to the parameter list. LoD 3 provides additional details on the tree branches, i.e., 2nd level branches that are directly connected to the main stem. LoD 4 includes bushes around the tree and provides further details on the tree branches, such as the 3rd level branches that connected to the 2nd level branches. LoD 5 represents a 3D tree model with the greatest amount of details. Tree leaves are added to the model and all branch and bush details are represented. The LoDs from 1 to 5 are illustrated in Fig. 3. The parameters included in the different LoDs and their predecessors are summarized in Table 1.

The 3D tree models that are used in forest inventories are mainly LoD 1, 2 and 3. Conventional forest inventories produce LoD 1 tree models. The DBH and tree height of all or selected trees in a sample plot are manually measured. LoD 2, i.e., a 3D stem model, holds a primary position in forest inventories because most of the tree volume, biomass and value are concentrated in the stems. LoD 3 is important and describes many timber quality aspects. Models at LoD 3 are challenging to construct at the plot level because the establishment of LoD 3 requires good data coverage from different viewpoints which leads to a rapid cost increase in data collection. LoD 3 to 4 are used in single tree modeling where more detailed information on tree branches are required. LoD 5 tree model is usually studied in computer graphics; TLS data is currently not suitable for recording the high level of tree details required, e.g., all leaves.

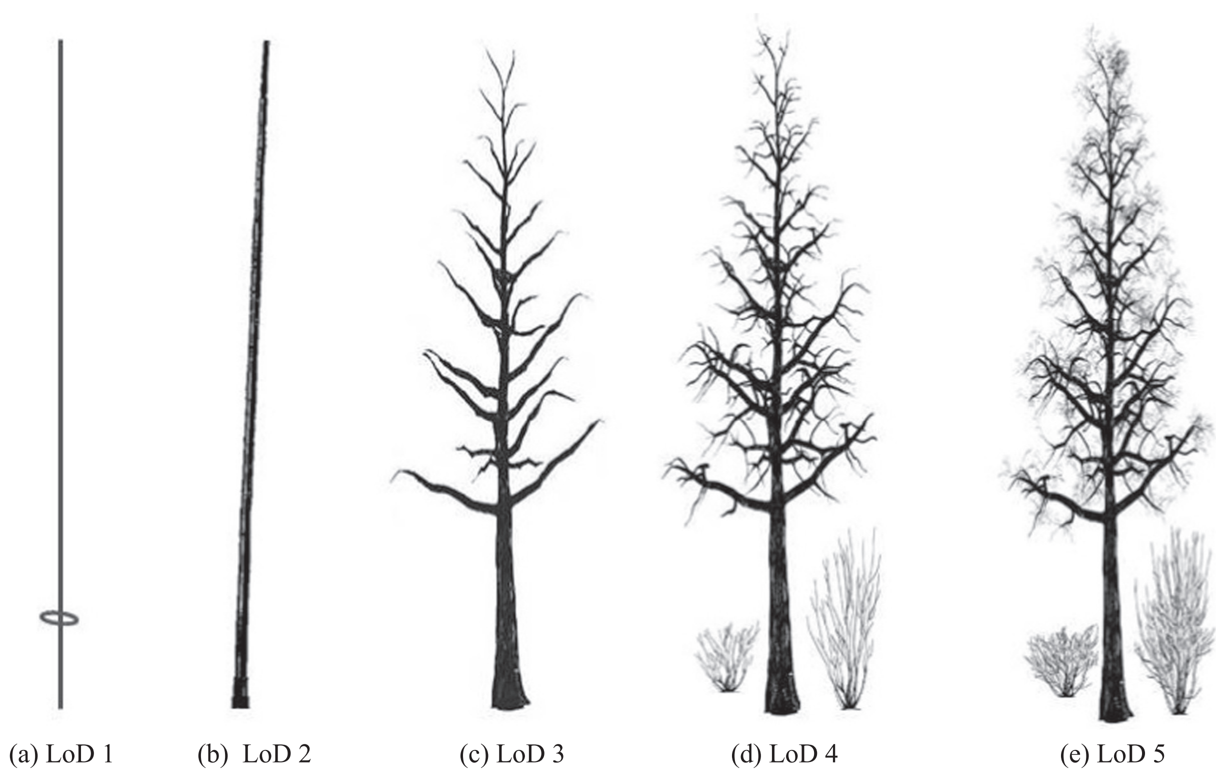

Fig. 3. Levels of details of the 3D tree model.

Table 1
The parameters and predecessors in the different levels of details of the 3D tree model.

Level	Details: Parameters	Details: Predecessor included
LoD 1	• Tree height • DBH	
LoD 2	• Tree position • 3D model of the main stem	LoD 1
LoD 3	• 2nd level branches (directly connected with the main stem)	LoD 1 + LoD 2
LoD 4	• 3rd level branches (connected with the 2nd level branches) • Bushes	LoD 1 + LoD 2 + LoD 3
LoD 5	• Leaves • More details of branches (higher level branches) • More details of bushes	LoD 1 + LoD 2 + LoD 3 + LoD 4

3.3. Expected applications

In forest inventories, TLS is mainly used in sample plot measurements, Stand-level Forest Inventories (SFIs) and the establishment of allometric models.

3.3.1. Sample plot measurement

One main application of TLS in forest inventories is the plot-level measurement, which provides the required attributes for, e.g., National Forest Inventories (NFIs). In NFIs, tree attributes, such as the DBH, species, tree class and canopy layer are measured from every tree, and more attributes such as the tree height, diameter at six meters (D6), age, bark thickness, lengths of timber assortments and damages are measured from sample trees, e.g., every seventh tree. Typical requirements on the accuracy level for those attributes are 0–2 cm for DBH, 0.5 m for tree height, 1–3 cm for upper diameters (e.g., D6), 0.5–2 m for tree locations, 10–20% for volume and biomass, 5 years for age and 100% for tree species.

TLS is expected to provide part of those required attributes of individual trees in the sample plot using automated methods. It is more straightforward for TLS to collect structural attributes of stems and canopies, such as the stem curve, the canopy layer and the timber assortments at the required accuracy level, but it is still challenging for TLS to measure other non-structural attributes such as the age and the bark thickness. The species remained as a main challenge to TLS, and solutions are expected from the new generation of multi- and hyper-spectral scanners. More information on the state of the art for the TLS-based tree attribute extraction can be found in Section 4.

3.3.2. Stand-level inventories (SFIs)

From the forest owner's point of view, stand-level forest data provide the most important information, which is used in management plans and operational forestry (e.g., harvesting). Currently, stand-level forest information consists of mean forest attributes predicted using the so-called area-based approach (ABA), where forest attributes in a 16-by-16 m grid are predicted and stand-level attributes are aggregated based on the grid cells within each stand. This approach requires a vast number of sample plots as training data. Stand-level attributes have also been estimated using relascope measurements from multiple locations within each stand. Relascopes can be used to measure the basal area of the surrounding trees, which can then be used to estimate volume (m^3/ha) based on knowledge of the tree species and their heights.

TLS could be used to acquire plot-level forest measurements required in ABA, e.g., tree model at the LoD 1. In addition, TLS could provide more attributes, such as quality and more detailed stem curve information and timber assortments at the LoD 2 and 3, which are not feasible to determine in the conventional field measurement. Alternatively, TLS could also be used in the multi-scan or MSS modes to collect data from the whole forest stand, which would provide an accurate and detailed description of the stand. The downsides of this approach are the costs of the data acquisition and the substantial increase in computing power required for the data processing and stand modeling.

3.3.3. Establishment and update of allometric models

Allometric models establish a relationship between tree attributes, typically between attributes that are practically measurable and non-measurable attributes, such as DBH and tree height or biomass. Allometric models are conventionally constructed through the destructive sampling of each sample tree, which is labor intensive and expensive. Because of the high cost of the model development, models only exist for certain areas and tree species. Using an allometric model in areas with different climatic, geographic and silvicultural conditions to those where the models were developed may lead to large errors in the estimates (Liang et al., 2014).

TLS could be a vital option for acquiring data for developing new allometric models. TLS has a rapid, non-destructive and automated measurement principle and is capable of measuring millimeter-level detail. These properties perfectly match the requirements for developing allometric models. More importantly, updating allometric models will become easier because of the decrease in the cost of model construction. The 3D tree models utilized for allometric modeling mostly cover the 3D tree model at LoDs 1 to 3.

In future, estimating tree attributes from TLS may reduce the need for maintaining local allometric models because many tree attributes will become directly measurable. However, in areas or applications where TLS is unavailable, allometric models are still the most practical way to predict tree attributes.

4. Evaluation of tree attribute estimations utilizing TLS

The results listed in this section summarize the state-of-the-art research from representative papers. However, this is not a rigorous comparison. The results depend on many factors, such as the forest structures, the instrument employed and the processing methods, which are different in the different papers.

4.1. Stem detection and stem density

The detection of individual tree stems is a fundamental process in sample plot measurements. The stem detection accuracy of the single-scan TLS data at the plot level reported in previous studies is summarized in Table 2. The detection rate decreases as the stem density increases. In sparse forests with a stem density of 200–400 stems/ha, above 80% of all trees within a plot can be located.

Table 2
Summary of the stem detection accuracy of the single-scan method reported in previous references.

	Plot			Result
	Number	Size	Density (stems/ha)	Detection rate (%)
Thies and Spiecker (2004)	1	~30 × 30 m	555.6	22
Maas et al. (2008)	3	15 m radius	212–410	86.7–100
Strahler et al. (2008)	1	50 m radius	130	40.2
Brolly and Kiraly (2009)	1	30 m radius	753	62.9–72.3[a]
Murphy et al. (2010)	18	30 × 33 m or 25 × 40 m	207–570	59
	15	10–20 m radius	153–326	82
Lovell et al. (2011)	2	20/50 m radius	124/477	54/68
Liang et al. (2012b)	9	10 m radius	509–1432	73
Liang and Hyyppä (2013)	5	10 m radius	605–1210	73.4
Olofsson et al. (2014)	16	20 m radius	358–1042	73.3

[a] Three detection methods were discussed.

In high-density forests with a stem density above 1000 stems per hectare, the stem detection rate was approximately 70%.

In Yao et al. (2011), tests were carried out in 28 circular plots of 20–25m radius. The average stem detection rate within all test plots was 42%. In Lindberg et al. (2012), tests were carried out in 6 sample plots, which were 80 × 80 m in size with a stem density of 519–663 stems/ha. The average stem detection rate within all test plots was 45.3%. In Astrup et al. (2014), tests were carried out in 162 circular plots with an 8.92 m radius in twelve stands with a stem density of 168–1050 stems/ha. The stand-level stem detection rate varied between 60% and 90%.

Within a sample plot, the detection accuracy using single-scan TLS has been reported to be a function of the range. In Liang et al. (2012b), the detection rate in 9 circular plots with a 10 m radius was reported to be 73%. When using a range of 5 m, the accuracy improved to 85%. In Astrup et al. (2014), the fitted detection functions indicated that the decrease in the detection rate was generally very pronounced at distances of approximately 6 m. The detection rate decreased with increasing distance from the scanner in single-scan TLS was confirmed in Olofsson et al. (2014).

Tree detection rates using the multi-scan mode vary between 62.1% and 100% depending on the forest structure and scanning setup, e.g., in Maas et al. (2008). Similar tree detection rates can be achieved using MSS and the multi-scan mode as shown in Liang and Hyyppä (2013). The forest structure has a major impact on the tree detection rates as showed in Kankare et al. (2015). Semi-automated methods were also proposed, e.g., in Eysn et al. (2013), for tree structure mapping using multi-scan data.

4.2. DBH measurements

DBH is the most frequently measured and utilized tree parameter and is considered to be the most important parameter in forestry. The accuracy of the DBH measurements using the single-scan approach at the plot level is summarized in Table 3, as reported in previous references.

In Yao et al. (2011), the DBH estimation results were reported at the tree level and mean plot level from the above-mentioned 28 plots. The root mean squared error (RMSE) of the DBH estimation was 7.6 cm and 2.4 cm, respectively. In Liang et al. (2012a), the DBH estimation results from 5 plots are reported at the tree level. The bias was 0.2 cm, and the RMSE was 1.3 cm. In Lindberg et al. (2012), the DBH estimation results were reported at the tree level from the above-mentioned 6 sample plots. The bias of the DBH estimation in that study was 0.2 cm, and the RMSE was 3.8 cm.

In Maas et al. (2008), a DBH accuracy of 1.5 cm was reported using multi-scan data from a 140-year-old forest. In Kankare et al. (2015), automatic DBH measurements from the multi-scan TLS data for diverse forest conditions were reported. The DBH accuracy varied between 1.4 cm and 2.0 cm with an overall accuracy of 1.7 cm. In Liang and Hyyppä (2013), 5 circular plots of 20-m radius were measured using the MSS approach. The RMSE of the DBH estimation was 0.9–1.9 cm.

The results from studies of different types of forests are highly variable, indicating the need for more research on this topic.

4.3. Tree height measurements

Tree height measurements using TLS for forest inventories have not been thoroughly studied. This is most probably because the uncertainty of the visibility of treetops in TLS data. Previous results have shown that tree height is typically underestimated and that the magnitude of the estimation error is typically several meters. The results of the tree height measurements are summarized in Table 4, as reported in previous references.

In Moskal and Zheng (2011), tree heights were measured from single-scan TLS data in city forests. The RMSE of the tree height estimation was 0.75 m at a tree level.

The direct measurement of tree height is very difficult because treetops are commonly shadowed by other trees or parts of the crown of the measured tree in the point cloud, i.e., the wide crowns of tall trees do not allow a nearby scanner to detect the exact treetops. The observation of tree tops from TLS data has been reported for sparse sample plots using several scans, e.g., in Huang et al. (2011) and Fleck et al. (2011). However, finding treetops from TLS data in dense sample plots remains a challenge.

A topic that needs more discussion is the impact of the scanning resolution on the possibility of adequately capturing treetops by taking into account the slant range effect. Reliable height measurements require point spacing at a 1–2 cm level at the treetops, which allows for the possibility of obtaining a hit on the smallest top branches. The multi-scan and MSS approach would improve

Table 3
Summary of the plotwise DBH estimation using the single-scan data reported in previous references.

	Plot			Result	
	Number	Size	Density (stems/ha)	Bias DBH (cm)	RMSE DBH (cm)
Maas et al. (2008)	3	15 m radius	212–410	−0.7 to 1.6	1.8–3.3
Brolly and Kiraly (2009)[a]	1	30 m radius	753	−1.6 to 0.5	3.4–7.0
Liang and Hyyppä (2013)	5	10 m radius	605–1210	−0.2 to 0.8	0.7–2.4
Olofsson et al. (2014)	16	20 m radius	358–1042	0.6	2.0–4.2

[a] Three detection methods were discussed.

Table 4
Summary of the plotwise tree height estimation reported in previous references.

	Plot		Data	Result	
	Number	Density (stems/ha)	Scan mode	Bias (m)	RMSE (m)
Huang et al. (2011)	1	212	Multi	−0.3	0.8
Hopkinson et al. (2004)	2	465, 661	Multi	−1.5	
Maas et al. (2008)	4	212–410	Multi/single	−0.6[a]	4.6[a]
Fleck et al. (2011)	1	392	Multi		2.4[b]
Liang and Hyyppä (2013)	5	605–1210	MSS	1.3	2.0–6.5
			Single	0.6	1.4–4.3
Olofsson et al. (2014)	16	358–1042	Single	−0.1	4.9

[a] For 9 selected trees.
[b] For 45 selected trees.

the possibility of capturing treetops in the point cloud data. On the other hand, studies have shown that canopy penetration saturates at angles of 23–27 degrees for airborne laser scanning (ALS), also known as airborne LiDAR. The same is expected to hold for TLS where the traverse path is reversed.

Currently, the magnitude of the estimation error implies that the results of tree height estimation using TLS data are not yet acceptable for operational forest inventories. More research is needed to investigate the accuracy of TLS-based tree height estimation. A possible solution for accurate tree height measurements in sample plots is the combination of ALS and TLS observations, where tree heights are measured using the ALS point cloud and the tree positions are estimated using the TLS point cloud. This possibility should be studied in the future.

4.4. Stem curve measurements

The tree stem curve, or stem taper, depicts the tapering of the stem as a function of the height. The tree stem curve holds a significant position in forestry, as it is one of the most important attributes for defining the stem value.

The non-invasive measurement of stem curves using TLS has not been intensively studied. Pioneering work included nine pine trees studied in Henning and Radtke (2006b) and one spruce tree studied in Maas et al. (2008). The RMSE of the stem curve measurements was 4.7 cm in Maas et al. (2008) using single-scan data.

In Liang et al. (2014). Twenty-eight trees, i.e., sixteen pine and twelve spruce trees at different growth stages, were studied using multi-scan data. The stem curves were automatically measured from the TLS point clouds with a mean bias of 0.15 cm and a mean RMSE of 1.13 cm at the tree level. At their maximum values, the diameters were between 50.6% and 74.5% of the total tree height, with a mean of 65.8% for the pine trees and 61.0% for the spruce trees. For comparison, the stem curve was also manually measured from the same point cloud data. The manual measurement yielded a mean bias of 0.44 cm and a mean RMSE of 1.03 cm at the tree level. The highest measured diameters ranged between 7.6% and 67.9% of the total tree height, with a mean of 47.1% for the pine trees and 27.8% for the spruce trees.

These results show that the TLS data and automated processing have the capability of accurately measuring the lower and most valuable part of stems at different growth stages. The automated processing clearly provided more diameter measurements at the upper part of the stems compared with the manual measurements using the same data. The difficulty associated with the manual measurements from the point cloud data is that the stem edges are difficult to locate when the stem is partly blocked in the data by other objects, e.g., branches.

The DBH and stem curve of the study trees are nowadays commonly estimated using the same procedure. In the future, the stem curve will become a measurable attribute for every standing tree using TLS in forest inventories, similar to other attributes widely used, e.g., DBH and tree height.

4.5. Stem volume estimation

The stem volume of six beech trees was studied up to a height of 10 m in Pueschel et al. (2013). The volume from the multi-scan TLS showed deviations that ranged from −2% to 6%, and compared with −34% to 44% for the single-scan.

In Astrup et al. (2014), stem volume estimation using single-scan TLS was reported. The bias of the automated estimates for spruce, pine and birch trees was 68.0, 14.9 and 24.1 dm^3, with corresponding RMSE values of 175.1, 131.5 and 76.2 dm^3, respectively. Harvester-head-measured estimates were used as a reference for these evaluations, which contained some measurement error related to calibration and slip. Stem volumes were also estimated from the allometric volume functions (as functions of DBH and tree height). In general, the estimates of the stem volumes from these three methods were similar.

The stem volume was calculated using the automatically measured stem curve in Liang et al. (2014). The bias of the automated stem volume estimation was −0.9 dm^3 and −12.5 dm^3 for pine and spruce trees, respectively. The corresponding RMSE was 24.2 dm^3 and 34.9 dm^3, and RMSE% was 8.9% and 9.8%. The performance of the volume estimates was evaluated by comparing this volume to the volume predicted using the Finnish nationwide allometric volume models developed in Laasasenaho (1982). The results show that the developed automated stem volume measurement method is as accurate as the best operationally used nationwide allometric volume models.

Notably, volume estimates from TLS data do not require any predictors. All features are automatically retrieved from the point cloud. In fact, the sampling of tree attributes such as tree height is typically applied on a plot level because of the difficulty of accurately measuring tree heights using conventional measurement tools. Therefore, less accurate estimates can be expected in field inventories using allometric volume models and inaccurate predictors.

In general more studies begun to show that the estimation of the stem volume from TLS is as accurate as allometric volume models and destructive measurements.

4.6. Biomass estimation

Biomass estimation typically relies on allometric models as a function of tree species, DBH and tree height, provided biomass models exist for a specific target area.

The automatic measuring of stem biomass using TLS was reported in Yu et al. (2013). Stem biomass was predicted based on a model developed from TLS estimates and was compared with field measurements, as well as a biomass equation. The biomass equation produced an RMSE% of 17.9%. For the model using the reconstructed stem and corresponding derived stem volume as the predictor, an RMSE% of 12.5% were achieved. A similar approach could also be utilized for branch biomass estimation if the point cloud of branches is sufficiently dense.

Kankare et al. (2013) utilized metrics derived from TLS point cloud data to predict biomass components (stem and branches). The results showed that branch biomass especially was significantly improved compared with the existing biomass models. This conclusion was confirmed in Hauglin et al. (2013). The overall accuracy of the total above ground biomass was 12.9% and 11.9% for Scots pine and Norway spruce, respectively. In Calders et al. (2015), the above aground biomass was estimated for 65 Eucalyptus leucoxylon, microcarpa and tricarpa using multi-scan TLS. An RMSE% of 9.7% was reported.

The use of TLS measurements as a reference for an ALS-based branch biomass model was studied in Hauglin et al. (2014). Only a small increase (3%) in the accuracy of the crown biomass estimation was recorded when TLS was used in ALS model training in comparison with the estimation based on the ALS-derived DBH and height using existing allometric models.

These results indicate that TLS measurements are capable of assessing tree biomass with high automation and accuracy. TLS data have a high potential to improve the establishment of the tree biomass. Previously, this has not been widely studied. To collect reliable reference data is a bottleneck.

4.7. Stem quality

Timber quality is a vital attribute of forest management planning due to its effect on the timber value and production potential.

The distribution and size of the dead branches along the stem and stem rot caused by, e.g., fungus, are the most influential tree-level attributes that affect tree quality.

TLS has shown potential for the measurement of the stem form (taper, sweep and lean) (Pfeifer and Winterhalder, 2004; Liang et al., 2014) and bark characteristics (Kretschmer et al., 2013). In Schütt et al. (2004), it was tested to detect and classify wood defects from TLS data. In Stängle et al. (2014), it was indicated that external bark quality attributes could be linked with the internal quality of logs. In Kankare et al. (2014), various tree quality features of Scots pine were measured using TLS data. The RMSEs for the lowest living and dead branches were 9.6% and 42.9%, respectively. The trees were also classified into three operationally important quality classes (high-quality timber, timber and pulpwood) with accuracies of 95.0% and 83.6% based on field- or TLS-measured tree attributes, respectively. The classification accuracies decreased slightly if the number of quality classes was increased to five, which is used in NFIs.

The prediction stem quality from TLS data was recently discussed. More emphases should be put on the evaluation of the stem quality from TLS data in coming years.

4.8. Change detection

Changes to forests caused by natural forces and timber harvesting constitute an essential input for many applications based on the use of permanent sample plots. While many studies focus on retrieving tree attributes, recording the changes in forest plots using TLS data has not been conducted in details.

The automated detection of forest structural changes over time using TLS data was reported in Liang et al. (2012a). In five forest plots, 90% of the tree stem changes could be automatically detected from the single-scan TLS data. These changes accounted for 92% of the change in basal area. The bias of the DBH estimated for the changed trees was 0.2 cm, and the RMSE was 1.3 cm.

In Srinivasan et al. (2014), tree biomass changes were discussed in three pine-dominated plots. TLS data were collected at a three-year interval using the single-scan TLS. The reference of the above ground biomass was calculated using a national equation, as a function of DBH. The change in the above ground biomass was calculated using three methods, which yielded RMSE values between 10.1 kg and 13.0 kg at the tree level.

In Mengesha et al. (2015), the tree volume increment over a two-year period was evaluated using TLS data and conventional measurements. The mean difference in the average plot volume increment between the conventional measurements and TLS data was 6.0% (4.8 m^3/ha) when only the trees that were visible to the scanner were analyzed. The difference increased to 8.1% (7.0 m^3/ha) when all the trees within the sample plots were evaluated.

These results indicate that major changes and associated changed features can be documented using multi-temporal TLS data.

5. Point clouds from TLS and other technologies

TLS was the only practical tool to collect terrestrial point cloud data in a forest environment ten to fifteen years ago. In the last five years, more instruments have become capable of producing similar point clouds. This trend continues, and new possibilities have been introduced that may change the landscape of forest inventories in the coming years.

5.1. Mobile and personal laser scanning

Mobile laser scanning (MLS) became a new source of terrestrial point cloud data after 2010 (Hyyppä, 2011). Research is at an early stage, such as in (Lin et al., 2010; Holopainen et al., 2013). MLS is a multi-sensor system operating on a kinematic platform. The laser component consists of one or more laser-based-measurement instruments. The positioning system typically includes a Global Navigation Satellite System (GNSS) receiver and an inertial measurement unit (IMU). The platform is typically a cross-country vehicle, such as an all-terrain vehicle or skidoo.

Personal laser scanning (PLS) (Hyyppä et al., 2013; Liang et al., 2015) is becoming possible due to the rapid sensor miniaturization. In PLS, the positioning and scanning instruments are similar to MLS and all of these instruments are carried, e.g., worn or held, by the operator. Terrestrial point cloud data are collected simultaneously as the operator walks through the inventory site.

Both MLS and PLS data are georeferenced. However, the point accuracy of these mobile systems is at a centimeter level and highly influenced by the GNSS signal coverage, which is quite instable under forest canopies. The advantage of MLS and PLS is the possibility of mapping large areas. In principle, a 5 ha corridor area can be covered in 15 min using MLS/PLS. The actual speed depends on forest conditions. The overall stem-mapping accuracy using MLS and PLS ranges between 80% and 92%. The bias% of the DBH estimations varied between −2% and 5%, and the RMSE% varied between 8% and 29% (Liang et al., 2015; Ryding et al., 2015). These results are comparable with what achieved using multi-scan TLS in sample plots with fixed radius.

5.2. Image-based point clouds

Point clouds reconstructed from small baseline (highly overlapping) images became practically available in the late 2000s due to the rapid evolution of computing hardware (e.g., CPUs and GPUs) and further improvements of the algorithms (e.g., structure from motion or advanced image-matching algorithms). It was shown lately that forest field plots could be measured using a consumer camera with a 360° full-perspective image-based point cloud. In typical field data measurements, an operator walks around the plot and captures highly overlapping images using a hand-held camera.

In Liang et al. (2015), a sample plot was mapped from two mapping paths located inside and outside of the plot, and different landscape/portrait image configurations were used. Five image point clouds were generated and compared. The overall detection accuracies of the image-based point clouds varied between 60% and 84%. The bias% and RMSE% of the DBH estimation were −3.6% to 8.5% and 8.0–18.9%, respectively. The same plot was also measured using PLS and MSS TLS approaches. The overall detection rate of PLS was 92% compared with 100% in MSS TLS. The bias% and RMSE% of the DBH estimation using PLS were 0.6% and 8.0%, respectively. The bias% and RMSE% of the DBH estimates using MSS TLS were 0.8% and 9.7%, respectively.

Alternatively, a point cloud of trees can be generated from a fixed view point using specific camera configuration, e.g., several cameras that have a certain displacement. In Forsman et al. (2012), such a multi-camera system was described. Five calibrated digital cameras were installed on a rig and images were acquired simultaneously. A point cloud can be generated from the fixed viewpoints similar to that generated from a moving scenario. The DBHs of individual trees in the view of the cameras were estimated with a RMSE of 2.1 cm.

5.3. Characteristics and perspectives of different data sources

Currently, TLS, MLS, PLS and image-based point clouds, as well as other image applications, are all available for conducting forest inventories. Thus far, TLS has been shown to be capable of providing the most accurate tree attribute estimates among various point cloud or image techniques.

Table 5
Comparison of image-based, TLS, MLS and PLS point cloud data.

		Image-based	TLS	MLS/PLS
Equipment	Size	✓		
	Weight	✓		
	Price	✓		
	Operational range		✓	✓
Field measurement	Speed			✓
	Complexity of point cloud generation		✓	
	Mobility	✓		✓
Attribute estimates	Accuracy		✓	
	Wood quality estimation		✓	

MLS compensates for the main limitation of TLS, i.e., the lack of mobility. PLS has even greater mobility than MLS. MLS and PLS have the potential to significantly increase the field mapping efficiency and the capability of collecting inventory data over large areas. To date, the sizes of forest sample plots are small because of the unacceptably high cost of collecting individual tree attributes in large sample plots. MLS and PLS make it possible to map large forested areas rapidly and conveniently. In the future, the visible area beside a single strip may serve as a forest plot. For example, a 20–50 m long and 6–20 m wide strip may be used as a plot, especially if ALS data are also utilized. Areas corresponding to visible trees will then to be utilized as the effective plot area.

The main advantage of the image-based point cloud is that the data can be collected using low-cost, low-weight and small sized hardware that is affordable and easy to use for both professional and non-professional users. In addition, there is free software for the processing of these data. Fully functioning software is being developed, which may have a cost associated with it when it becomes available. In the future we may see a situation where the average person will be capable of carrying out forest inventories. Therefore, the cost of field plot inventories could be significantly reduced and the number of field plots may be greatly increased.

Image-based, TLS, MLS and PLS point clouds were compared in Table 5, based on the comparison in Liang et al. (2015). The favorable characteristics of the forest data collection are marked.

6. Discussion and outlook

TLS attracted interest as a technique for obtaining detailed tree attributes for forest inventories soon after its introduction. The initial motivation for using TLS is to replace manually measured tree attributes with those retrieved automatically from the TLS data. Gradually, research has shown that TLS is capable of deriving tree attributes that are not conventionally feasible to measure and is capable of measuring forests in a way that is different from conventional inventories. These findings indicate that TLS could be used beyond the current scope of forest inventories. Currently, there is no agreement on whether TLS will result in incremental changes or revolutionary advances. To understand the future of TLS in forest inventories, some key questions need to be answered and these answers will shape the perspectives of research and practices.

6.1. Single-scan as an effective way?

In forest inventories, there is a need for a large amount of field reference data and a need to have all trees mapped within the smallest reference unit. It is difficult and costly to manually measure a large number of plots in the field. TLS is anticipated by foresters to operate in the same way as conventional tools, i.e., to measure all trees in a plot.

The discussions thus far have been based mainly on this understanding. Consequently, the single-scan approach is considered a less accurate approach compared with the multi-scan and MSS approaches, because it only measures approximately 70% of the trees in dense forests, though the accuracy of the tree attributes measurement (e.g., DBH) is comparable with the other two scan modes.

One research topic is therefore how to incorporate corrections for the omission bias to estimate plot-level tree attributes by constructing a model based on the relationship between the trees in the visible area of the single-scan TLS and the trees in the whole sample plot. Corrections for undetected trees were derived based on geometry in Strahler et al. (2008) and Lovell et al. (2011). Ducey and Astrup (2013) suggested that tree size as well as multiple stand structural characteristics may be factors to build the model. In Astrup et al. (2014), three bias correction approaches were tested and similar results were achieved.

Another possibility is to use the TLS field plot, which has been less discussed thus far. In the TLS field plot, all visible trees from the center scanning position are used as a reference, rather than all trees in the sample plot. The TLS field plot should work especially when using individual tree based forest inventories, provided the selected trees are representative of all the trees in the forest. For example, single-tree-level references can be collected from the TLS field plot and used to train airborne data; tree attributes of all the trees inside the stand can thus be estimated from airborne remote sensing data. Single-scan data can also be collected from multiple locations within forest and all the trees visible in the data can be used to predict the mean values in the stand. This protocol needs to be further explored and verified for feasibility and validity. If it works, it may largely change the way in which forest plots are measured.

6.2. The possibility of the large sample plot

A permanent sample plot in NFIs is typically a small area of the forest, e.g., a circular area with a 10 m radius, because it is very demanding and mostly impractical to collect forest inventory data over a large area using conventional measurement methods, especially if the stem count per hectare is high. However, large sample plots are desirable because a large sample plot not only provides a more accurate and comprehensive understanding of the forest environment but also facilitates the registration of ground references and airborne remote sensing data (Liang and Hyyppä, 2013).

The multi-scan TLS approach can be used to document large sample plots if automated registration methods work. This can also be achieved by using the MSS approach. The challenge lies in the automatic matching of two data sets with large radii, where the common trees between two neighboring scans are limited and may further decrease as the plot size increases because the stem-detection accuracy decreases with an increase in the range of the single-scan approach. Previous research showed that trees far from the scanning position can be detected. The mapping radius was 30 m in Brolly and Kiraly (2009), 40 m in Lindberg et al. (2012) and 50 m in Lovell et al. (2011). If the detection accuracy does not decrease dramatically at the far end of the plot, it is possible to match two data sets with large radii. This possibility needs to be explored and the practical size of a sample plot for mapping a large area using TLS needs to be clarified.

In future, the size of the reference sample plots can be larger, or even considerably larger, than what is the current size. MLS and PLS have shown excellent capability in mapping large areas. TLS would still be an attractive solution for mapping large areas if it would be possible to do so based on a couple of statistic scans using multi-scan and/or MSS approaches with large radii. This is because TLS would have a similar capability of covering large areas and the equipment is cheaper than MLS and PLS.

6.3. Improving the understanding of the forest using TLS

In the past, efforts have focused on retrieving tree attributes at both the single tree and plot level. In the coming years, greater emphasis needs to be placed on research that focus on how to integrate these new detailed attributes into the value adding processing chain.

The retrieval of information on individual trees across large areas has been possible for a decade using ALS (Hyyppä and Inkinen, 1999; Persson et al., 2002). To date, sample plots and tree attributes, such as DBH and tree height, were measured to be used as a reference to train the ALS data. It is possible to train the ALS point cloud metrics for area-based variable predictions using more tree attributes extracted from the TLS point clouds, such as stem curve, volume and biomass. This new possibility has not been studied because acceptable results from TLS were just recently reported and an automatic processing of a large number of plots with diverse forest conditions is still missing.

The TLS data and automated processing techniques also offer new possibilities for improving wood procurement. For example, detailed stem quality information at the tree level, such as stem sweep and merchantable length, has become available through automated estimation. This information makes it possible to estimate the value of stems based on any desired specification, e.g., market prices. In addition to the estimation of stem value, it is also possible to plan the bucking of stems into logs using detailed stem form/shape data and thereby optimize the overall profit. It is important for this optimization to be performed before harvesting to enable the planning and maximization of log size and profit at the stand and forest estate levels. In the future, standing trees, rather than piles of stems in the vicinity of factories, would then serve as wood storage. The forest industry's supply chain can thus be optimized. New thinking for timber logistics and possibly stem identification and follow-up services will be required to ensure the cut stem is used as planned.

Meanwhile, the study of TLS technologies should be further strengthened. Studies are needed to estimate additional tree attributes, which extends the range of TLS applications and defines the future use of TLS. For example, tree species information is necessary for plot-level and stand-level estimates. TLS data have the potential to determine tree species using either spectrum or waveform data or 3D points. Lack of automatic tree species classification methods is limiting the use of TLS in sample plot measurements. Other tree attributes that are closely related to the tree volume and quality include the crown projection area and the first branch height. These topics have seldom been discussed thus far. Investigations should be made into the potential of applying TLS data to estimate these attributes of individual trees at a plot level.

Plot-level changes over time require further investigation. Some pioneer work on structure, volume and biomass changes was reported (Liang et al., 2012a; Srinivasan et al., 2014; Mengesha et al., 2015). More tests under diverse forest conditions, such as different regions, terrain, species and management activities, are needed. Further studies are also needed to calibrate the bi-temporal ALS data. The changes in the ALS data could be calibrated using information obtained from TLS in permanent sample plots, and bi-temporal ALS data could be used to map changes over a large area.

6.4. Challenges of using TLS in operational forest inventories

From a practical point of view, the best practices of applying TLS in forest inventories have not yet been established. The fixed scanning resolution in the TLS measurement results in a decreased spatial resolution as a function of the distance from the scanner. This measurement principle and the fact that occlusion effects are common in forest environments raise many practical issues, such as the maximum measurement distance under different forest conditions (e.g., structure, species, slope), the TLS setups (e.g., number, distances and geometry of the scanning locations), and the selection of scanners. Previous studies mainly concentrated on the new applications of TLS. Studies on the best practices associated with the use of TLS in forest inventories are insufficient.

Some recent research was reported on practical aspects of using TLS in forest inventories. In Ducey et al. (2013), visual interpretation indicated that a small-beam diameter led to better penetration through low branches and understory vegetation. In Trochta et al. (2013), two scanners located at a 40-m distance from each other were shown to produce the best results when compensating for the occlusion effects. The findings of these early studies need to be further validated in more diverse forest conditions and larger amount of sample plots.

Pre-scan preparations, such as the removal of lower tree branches and the clearing of undergrowth, were performed in some studies before the TLS campaigns. In some cases, such as in a pre-harvest inventory, pre-scan preparations are common because the undergrowth needs to be cleared for the harvester. In other cases, such operations are either unacceptable or undesirable, for example, in conservation areas where the damage of trees is forbidden, and in NFIs where extra field work should be minimized.

Currently, it is not clear whether pre-scan preparations are a necessary step in the TLS campaigns. Most of the studies attempted to develop an automated method without any pre-scan preparations (Simonse et al., 2003; Thies and Spiecker, 2004; Hopkinson et al., 2004; Watt and Donoghue, 2005; Maas et al., 2008; Tansey et al., 2009; Lovell et al., 2011). The impact of the pre-scan preparations is currently unclear. In Murphy et al. (2010), it was found that more extensive pre-scan preparations led to better tree attribute extraction results. In Mengesha et al. (2015), however, pruning of the lower branches did not improve tree recognition, and the number of (partly) occluded trees remained the same. The need and the impact of pre-scan preparations need to be clarified.

The knowledge of the best practices of applying TLS in forest inventories is currently missing. General guidelines are required for the utilization of TLS in an operational forest inventory.

6.5. Perspectives of using TLS for forest inventories

In general, there is sufficient evidence that TLS can be put into practice. The current bottleneck is that no commercial software is available and when it becomes available, it may be expensive. Previous research has focused on automated processing technologies. In practice, the operational process for using TLS data in forest inventories can also be performed in an interactive way. In such a context, automated tools are used to map all trees, construct preliminary 3D stem models at the LoD 2, and extract required tree attributes. Because most of the TLS data are dense, visual inspection can improve the quality of the tree attribute estimates after automated processing, e.g., improve models at LoD 2 to LoD 3. Limited, manually interactive work for all trees and plots is recommended to extract tree attributes that are not retrieved from automated processing. The amount of time spent on this would be beneficial.

Today, TLS is mainly studied from the perspective that the method will be used to automate inventories and the output is used to calibrate ALS or space-borne data. Additionally, the TLS point clouds could be extremely valuable to those planning silvicultural operations because these point clouds reveal a lot of details that are not provided by automated tools today. On the other hand, information is now available to enable the generation of new allometric models based on TLS data, provided the LoD-2 models are automatically constructed and manually checked, and other information is manually collected. Operational software allowing all of these operations would be extremely beneficial. Thus, the operational use of TLS in forest inventory is a complex process if all the benefits of the TLS data will be incorporated into the process.

7. Conclusion

In the last decade, steady progress in the study of the application of TLS in forest inventories has been witnessed. The tree attributes that can be automatically estimated from terrestrial point cloud data expanded from tree attributes that are widely used in forest inventories to those that are not measurable using conventional tools. The experiments on automated data processing were first conducted in homogeneous forests and have increasingly been conducted in forests with varying structures. The accuracy of tree attribute estimates based on TLS data was demonstrated to be acceptable for most countries, e.g., to be within 1–2 cm RMSE for DBH estimates, and these estimates could be as good as those based on the national allometric models. The developed methods, experiments and techniques have demonstrated that TLS can be practically used for collecting certain tree attributes in sample plots accurately.

After a decade of active research, TLS has not yet been accepted as an operational tool in forest inventories. Its application is hampered mainly by difficulties in the automation of the point cloud processing that provides convincing measurement results of the most important forest inventory parameters. Up to now, there is still a lack of automatic and accurate methods to detect some important tree attributes such as tree species and height, which need further studies. Other important factors that limit the use of this technology include the relatively high cost of the instrument, the limited software and the lack of personnel training. Additionally, it should be noted that acceptable results obtained from using TLS for forest inventories, from a forester's perspective, have only recently been presented. Therefore, it will take some time before foresters start using TLS operationally, and sufficient time is required to build the necessary software.

TLS used to be the only effective technique to acquire terrestrial point cloud data for forest inventories. In the last few years, mobile/personal laser scanning and image-based techniques have become capable providing similar 3D point cloud data, and have their own advantageous, e.g., lower cost when using image-based techniques and high efficiency when using mobile/personal laser scanning. Further studies need to demonstrate the added value of using TLS, which most probably comes from the highly accurate tree attribute estimates.

In the near future, TLS can be utilized in tree-by-tree measurements in sample plots, with the aim of supporting ALS-based forest inventories or National Forest Inventories. TLS will likely challenge the efficiency of conventional measurement methods. In other application where the estimation of diverse tree attributes needs to be very accurate, such as stem curve and above ground biomass measurement, TLS will likely have a good chance of changing the current measurement scenario.

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