Hyyti, Heikki; Lehtola, Ville V.; Visala, Arto

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Forestry crane posture estimation with a two-dimensional laser scanner

Heikki Hyyti¹,² | Ville V. Lehtola² | Arto Visala¹

¹Department of Electrical Engineering and Automation, Aalto University, Aalto, Finland
²Finnish Geospatial Research Institute, Masala, Finland

Correspondence
Heikki Hyyti, Department of Electrical Engineering and Automation, Aalto University, PL 15500, FI-00076 Aalto, Finland. Email: heikki.hyyti@iki.fi

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Abstract
Crane posture estimation is the stepping stone to forest machine automation. Here, we introduce a robust minimal perception solution, that is, one that uses minimal constraints for maximal benefits. Specifically, we introduce a robust particle-filter-based method to estimate and track the posture of a flexible hydraulic crane by using only low-cost equipment, namely, a two-dimensional (2D) laser scanner, two short magnetically attached metal tubes as targets, and an angle sensor. An important feature of our method is that it incorporates control signals for hydraulic actuators. In contrast to the previous works employing laser scanners, we do not use the full shape of the crane to estimate the crane posture, but, instead, we use only two small targets in the field of view of the laser scanner. Thus, a large share of the range data is useful for other purposes, for example, to map the surrounding environment. We test the proposed method in a challenging forest environment and show that the particle filter is able to estimate the posture of the hydraulic crane efficiently and reliably in the presence of occlusions and obstructions. During our comprehensive testing, the tip position was measured with average errors smaller than 4.3 cm whereas the absolute maximum error was 15 cm.

KEYWORDS
forestry, instrumentation, laser scanning, perception, position estimation

1 INTRODUCTION

Hydraulic cranes are widely used in various work machines, such as excavators (e.g., Dunbabin & Corke, 2006; Haga, Hiroshi, & Fujishima, 2001; Roberts, Winstanley, & Corke, 2003; Stentz, Bares, Singh, & Rowe, 1998), loader cranes (e.g., Cheng, Oelmann, & Linnarsson, 2011; Hansen, Andersen, & Conrad, 2001; Pedersen, Andersen, & Nielsen, 2015), forest harvesters (e.g., Lindroos, Ringdahl, La Hera, Hohnloser, & Hellström, 2015), forwarders (e.g., Ortiz Morales et al., 2014; Westerberg & Shiriaev, 2013), and other forest machinery (e.g., Kalmari, Backman, & Visala, 2014; Kalmari, Pihlajamäki, Hyyti, Luomaranta, & Visala, 2013b). Compared to robotic manipulators, hydraulic cranes are lightweight and flexible so that they can lift large weights compared to their own size without breaking. On the other hand, flexibility increases the difficulty of estimating the position of the boom tip, that is, the place to mount a tool. This difficulty is further increased by that forestry cranes that are usually redundant manipulators with the position of the boom tip determined by more variables than it has degrees of freedom (x, y, z vs. three angles of rotation and one linear displacement position) (Kalmari et al., 2013b; Westerberg & Shiriaev, 2013).

For automation purposes, it is important to know the full six-dimensional pose of the mounted tool. This problem can be split into knowing the pose of the platform with respect to world coordinates, knowing the posture of the crane with respect to the platform coordinates, and knowing the tool pose with respect to the boom-tip coordinates. Here, we focus on the second one because it is sufficient in most cases relevant to forest machines to know the boom-tip position relative to the machine. Determining postures for robotic manipulators has a long history in industrial robotics, where this is done typically by measuring joint angles for rigid manipulators. However, forestry cranes are not rigid manipulators as noted earlier. Instead, they bend and vibrate. These effects are hard to model, as even the static bending is rarely known in forestry operations, which include lifting various tools and trees with unknown weights.

Owing to the above-mentioned challenge, the instrumentation and automation of forestry cranes has not been attempted but until recently (e.g., Cranab, 2015; Kalmari et al., 2013b; Suuriniemi, 2013;
Westerberg & Shiriaev, 2013). Without sensing devices, all feedback control is left to the the operator. This is problematic as the accuracy of control, working speed, and the achieved efficiency depend totally on the skill of the machine operator (Lindroos et al., 2015; Ortiz Morales et al., 2014). Manufacturers have started to solve this problem by adding sensors that are used to measure the positions of the crane joints (see, e.g., Cranab, 2015; Suurinimi, 2013). However, these systems are expensive and need a lot of sensors and cabling for the crane but still cannot account for the flexibility when lifting unknown weights.

If the posture of the hydraulic forestry crane (i.e., the configuration of the crane and the boom tip position) could be measured with a sufficient accuracy, it would enable quite many new possibilities. Lindroos et al. (2015) list the following among others. First, the harvested timber could be traced more accurately to individual trees. Second, the harvester data could be used to update tree maps by recording the location and dimensions of each harvested tree. This data could be used as a reference for methods that are used to generate single-tree inventory maps from satellite and airborne imagery and point clouds. Third, the accuracy of tree removal in thinning operations could be increased by helping the operator to select the trees to be removed. Fourth, machine operators’ working speed, style, and skills could be estimated from the actual crane movements that could benefit operator training and guidance. Finally, the forest machine could be made more autonomous if the crane posture is known.

A method, which is able to observe the boom-tip position directly, would be preferred, since it is independent with respect to the flexibility of the crane. For example, optical and radio-frequency-based methods could be used. Ideally, this could reduce errors from decimeter to centimeter level, surpassing the industry-implemented solutions (e.g., Cranab, 2015; Suurinimi, 2013). On the other hand, optical and radio-frequency-based methods are faced with their own difficulties from the environment where forest machines are used. For instance, the measurement should be robust against occlusions on the line of sight caused by undergrowth, tree twigs, and leaves, since some operations, for example, cutting, include guiding the tool to the trunk, which may be covered by dense undergrowth. The method should also work well with an attached, freely hanging tool, for example, a grapple or a harvester head.

As machines are used throughout the year, the measurement setup should be weatherproof withstanding rain and snow, dust, and dirt and large changes in temperature (Lindroos et al., 2015). Direct sunlight, shadows, and the darkness at night and winter hinder the use of (passive) optical systems in a forest environment (Billingsley, Visala, & Dunn, 2008). Self-illuminating optical systems (e.g., laser scanners) are more robust with respect to changing lighting conditions. Therefore, we construct our system using SICK LMS 221 (SICK AG, 2006), which is a reliable and quite affordable weatherproof two-dimensional (2D) laser scanner. Naturally, any equivalent laser scanner can be used.

In this paper, we introduce a robust particle-filter-based method to estimate and track the posture of the hydraulic crane using only low-cost equipment, namely, our 2D laser scanner, two short magnetically attached metal tubes as targets, and an angle sensor (for the first joint, i.e., the slew angle). In addition, we present a simpler method without the probabilistic framework to highlight the advantages of the former one. In contrast to the previous methods employing laser scanners, we do not use (nor need) the shape of the crane to detect and measure the crane posture as described by Kashani et al. (2007, 2010), but instead we use minimal instrumentation—two small targets in the field of view of the laser scanner. This allows us to use the rest of the laser scanner data to simultaneously map the surrounding environment and produce a three-dimensional (3D) point cloud.

The motivation to enable the same instrumentation for measuring crane posture and observing surrounding environment comes from the idea that forest inventory data could be efficiently collected while operating in the forest. Traditionally, data for forest inventory information are collected from aerial and satellite images and laser scanning (Hyyppä et al., 2008). However, terrestrial and mobile 3D LIDARS are becoming more widely used in the field of forest inventory (Hyyppä, Jaakkola, Chen, & Kukko, 2013). Furthermore, forest machines have been studied as mobile mapping platforms, for example, by Miettinen, Öhman, Visala, and Forsman (2007), Öhman et al. (2008), and Hytyi and Visala (2013). Currently, commercial 3D LIDARS can provide accurate point cloud data (Schwarz, 2010), but they are quite expensive to be installed to machines operating in a forest for gathering data solely for forest inventory purposes. Therefore, there is either a need for low-cost solutions for acquiring 3D point cloud data under silvicultural operations, or alternatively, a need for attaining extra functionality to the more expensive 3D LIDARS. Our solution provides both. The combination of a low-cost 2D laser scanner and an angle sensor in the first crane joint forms a low-cost 3D LIDAR. Extra functionality is added for it by measuring the posture of the crane simultaneously.

As this is a scientific study, an accurate reference for the crane posture is required to validate our results. This turned out to be particularly difficult. To show that our method is robust against short-term occlusions, accurate continuous-time reference measurements are required. However, owing to the occlusions and interfering tree branches, we could not construct an external optical or a mechanical reference measurement system. Therefore, we decided to rely on a reference constructed from cylinder length measurements, a kinematic model, and a bending model for the crane. The bending model is incorporated to the kinematic model as torsional springs between rigid links (Pedersen et al., 2015). The reference was calibrated for certain conditions, which were fixed during our tests. Note that our solution omits the determination of the platform pose, including swaying of the machine and the bending of the pillar (i.e., the first section of the crane). If these were to be accounted for, the orientation changes of the laser scanner (fixed to the pillar) could be measured with, for example, a 3D inclinometer.

The rest of the paper is organized as follows: The next chapter describes the state of the art in posture measurement of a hydraulic crane. Then in the Methods section, we first introduce our forest machine, the minimal instrumentation, and forward kinematic equations. Second, we propose a simple algorithm (Method SD) to detect our scan targets, that is, certain size circular objects, from the 2D laser scanner data to estimate the crane posture. Third, we introduce our particle filter algorithm (Method CPPF) that also incorporates control signals for hydraulic actuators, to track the targets and to estimate
the crane posture. Fourth, we model the static bending of our crane boom due to gravity and show how to calibrate our setup to acquire a sufficiently accurate reference posture by using the hydraulic cylinder length instrumentation as proposed by Kalmari et al. (2013b, 2014).

In the Results section, the proposed methods are benchmarked in five different test scenarios. The first test is the easiest one without any obstacles in the field of view. The subsequent two tests are done near trees having a considerable amount of occlusions in the measurements. The fourth test is a really long test with a freely swinging tool that is attached to the tip of the boom. The fifth test is a simulated tolerance test against weather effects. Finally, we discuss the accuracy and the robustness of the proposed 5D and crane posture particle filter (CPPF) methods. We also show an example of a 3D point cloud, which is acquired during the above-mentioned testing.

2 STATE OF THE ART IN POSTURE MEASUREMENT OF A HYDRAULIC CRANE

In robotics, the posture of the manipulator is traditionally obtained by measuring angles between each rigid link in it and calculating the end-effector pose using a forward kinematic chain (Waldron & Schmiedeler, 2008). In addition to angle sensors, for hydraulic manipulators, joint angles can be measured using linear encoders attached to each hydraulic cylinder, and telescopic extensions (i.e., prismatic joints) can be measured with a length measuring device built within the joint (e.g., Cranab, 2015; Kalmari et al., 2013b; Lindroos et al., 2015; Suuriniemi, 2013).

Instead of using structures more familiar with industrial robotics, hydraulic forestry cranes are usually built flexible to optimize material usage and to keep their weight low (Pedersen et al., 2015). As may be expected, this results into significant bending that should be taken into account. Although there exist methods to estimate bending (e.g., De Luca & Panzieri, 1994), these methods need to have the right model parameters and predefined weights to avoid any end-effector displacement errors. However, these weights are bound to change as the crane is used to lift unknown loads. Therefore, there is a need for alternative methods to maintain a sufficient level of accuracy for the posture of the manipulator. Such alternative methods include observing the posture directly by using cameras, laser scanners, or inertial measurement units (IMUs).

Camera-based solutions have been demonstrated for excavators (e.g., Feng, Dong, Lundeen, Xiao, & Kamat, 2015; Mieliikäinen, Koskiinen, Handroos, Toivanen, & Kälviäinen, 2001; Mulligan, Mackworth, & Lawrence, 1989), for large tower cranes (e.g., Yang, Vela, Teizer, & Shi, 2012), for large rope-operated shovels (e.g., Corke, Roberts, & Winstanley, 1998; Lin, Lawrence, & Hall, 2010), and for underground mining machinery (e.g., Corke et al., 1998). The solution by Mulligan et al. (1989) is able to measure the posture of the crane without external targets like in the work by Mieliikäinen et al. (2001) or external cameras installed outside the crane, like in the work by Feng et al. (2015) and Yang et al. (2012). The solution by Lin et al. (2010) only estimates a sling angle using a stereo camera setup. Finally, in the work by Corke et al. (1998), instead of measuring the crane posture, the system automatically searches for a drilling hole by using an end-effector-mounted camera.

The literature on laser scanner–based solutions has been focused on estimating the posture of a very large rope operated shovel (e.g., Dunbabin & Corke, 2006; Kashani, Owen, Himmelman, Lawrence, & Hall, 2010; Phillips, Green, & McMee, 2016). Only Kashani et al. (2007) have tested scanner with a normal-sized excavator. Kashani et al. (2007, 2010) used a 2D scanner mounted vertically under the crane boom such that the boom and a tool (e.g., a bucket or a shovel) are visible in the point cloud from which the boom and the tool shapes are detected. Their method is reliable in the mining environment because there are rarely obstacles between the boom and the scanner allowing easier detection of the boom and the tool. Dunbabin & Corke (2006) have installed the scanner higher in the boom so that also the surrounding environment can be modeled at the same time as a pose of the dipper is estimated. Finally, in the work by Phillips et al. (2016), a 3D LiDAR is used for the same task by probabilistically fitting the dipper model into a measured 3D point cloud.

IMU-based solutions usually use one or multiple triaxial accelerometers and gyroscopes to estimate the orientation of the sensor with respect to the earth frame. In the work by Vihonen et al. (2013a, 2013b, 2014), the posture of a forestry crane similar to ours is estimated with low-cost microelectromechanical system IMUs. Their latest work includes an integrated kinematic model for the crane, and it uses multiple accelerometers and gyroscopes attached to the crane boom (Vihonen et al., 2016). The setup can reach up to 1° accuracy for lift and tilt (referred as transfer in our work) angles and can take bending into account. However, the length of the telescopic extension is significantly more difficult to estimate with only IMUs as Vihonen et al. (2014) reported. They can only reach centimeter-level accuracy when the telescopic link is contracted. While the crane is at maximum reach, the average error increases to 0.26 m. For this reason, other range measuring instruments are used for the prismatic joint. For example, Cheng et al. (2011) used sonar to measure the length of the extension link with an IMU instrumentation. In addition to estimating the posture of the crane, IMUs may also be used to estimate the pose of the end-effector, for example, a swaying tool attached to the boom tip (e.g., Kalmari, Hyyti, & Visala, 2013a).

In addition to optical or inertial measurements, also ultra wide-band radio frequency identification (UWB RFID) tags (Zhang, Hammad, & Rodriguez, 2011) and global navigation satellite system (GNSS) (Kim & Langley, 2003) have been used to measure the crane posture and the end-effector position. Zhang et al. (2011) studied UWB positioning of a construction crane for safety purposes, obtaining an accuracy of position of approximately 25 cm with active RFID tags. In their work, the transceivers were installed in the environment to guarantee good visibility between them and the tags. UWB techniques have since been shown to yield subcentimeter accuracies in an indoor-positioning competition (see Table 2 in Lymberopoulos & Liu, 2017). Therefore, UWB technologies could also have potential in crane posture estimation. For GNSS, the accuracy under the forest foliage is a serious limiting factor for the crane posture estimation. Kaartininen et al. (2015) have shown that a high-end integrated inertial navigation and GNSS receiver can achieve a 0.7-m accuracy under forest canopies. This is not
order providing $N_l = 721$ range measurements covering a field of view of $180^\circ$ with $0.25^\circ$ resolution at 18.75 Hz frequency, which is usually enough for estimating the crane posture. This combined set of measurements is referred to as a scan in the following.\footnote{Such a scan corresponds to a scan obtained from a 2D scanner functioning natively with a $0.25^\circ$ angular resolution.}

The two scan targets, which are magnetically attached metal tubes with a diameter of 60 mm, are shown in Figure 1 (B and C). They are tracked to estimate the posture of the crane (i.e., the inner boom between A and B and the outer telescopic boom between B and C). The first target (B) is placed onto the end of the transfer joint axle, and the second one (C) is mounted onto the side of the boom tip position, where the rotator link and the tool are mounted. They are always in the field of view of the 2D laser scanner. Their positions embody the minimum amount of prior knowledge needed to solve the crane posture (see Sections 3.1 and 3.2). Once the kinematic model and the laser scanner pose are known, the joint angles and the extension length can be estimated from the measured positions of the scan targets.

### 3.1 | Kinematic model of the forestry crane

In the previous work by Kalmari et al. (2013b, 2014) and Kalmari (2015), the position of the boom tip is solved using a forward kinematic chain of rigid transformations (Waldron & Schmiedeler, 2008) using joint angles that are estimated from measured lengths of hydraulic cylinders. This two-step process is briefed next for those parts needed in this work.

At the first step, the slew angle $\theta_1$ and the extension length $d_4$ are measured directly and the lift angle $\theta_2$ and the transfer angle $\theta_3$ are calculated from the cylinder lengths with the crane model (by Kalmari, 2015):

\[
\theta_2 = \arccos\left(\frac{\hat{l}_2^2 + \hat{l}_3^2 - \hat{d}_2^2}{2\hat{l}_2\hat{l}_3}\right) + \theta_{2b}, \tag{1a}
\]

\[
\theta_3 = \theta_{3b} - \arccos\left(\frac{\hat{l}_3^2 + \hat{l}_4^2 - \hat{d}_3^2}{2\hat{l}_3\hat{l}_4}\right) - \arccos\left(\frac{\hat{l}_5^2 + \hat{l}_6^2 - \hat{d}_4^2}{2\hat{l}_5\hat{l}_6}\right), \tag{1b}
\]

where

\[
\hat{l}_6 = \sqrt{\hat{l}_2^2 + \hat{l}_3^2 - 2\hat{l}_4\hat{l}_5 \cos(\gamma_{23} - \arccos(\frac{\hat{l}_3^2 + \hat{l}_4^2 - \hat{d}_3^2}{2\hat{l}_3\hat{l}_4}))}, \tag{1c}
\]

\[
d_2 = d_{2,\text{meas}} + d_{2,\text{bias}}, \quad d_3 = d_{3,\text{meas}} + d_{3,\text{bias}}, \quad d_4 = d_{4,\text{meas}} + d_{4,\text{bias}}.
\]

In Equation 1, $d_2$ is length of the lift cylinder, $d_3$ is length of the transfer cylinder, and $d_4$ is the extension length. All other lengths $l_1$, $l_2$, $l_3$, $l_4$, $l_5$, $l_6$, and $l_8$, and angles $\theta_{2b}$, $\theta_{3b}$, and $\gamma_{23}$ are constant parameters defined by Kalmari (2015), and their values are presented in Table 1. All cylinder lengths include a zero offset $d_{c,\text{bias}}$ and a measured length $d_{c,\text{meas}}$ for each cylinder $c$. Offsets are later calibrated under Section 4.2 and presented in Table 6.

At the second step, the boom-tip position $p_{\text{tip}}$ is computed from the previously defined joint angles and the extension length with the
Method SD: Simple target detector

Minimal perception setup

The method is designed to work accurately only in easy cases without obstructions in the laser scanner data. This method is later used to initialize the proposed particle filter (see Section 3.4) and to calibrate the system setup (see Section 4.2).

3.2 Minimal perception setup

Consider solving the joint variables from the measured crane posture using inverse kinematics. Equation 2 has only three measurements (coordinates of the boom tip position: \(x, y,\) and \(z\)), but there are four independent variables (three joint angles and the extension length).

Thus at least one more independent measurement of the crane posture is required in addition to the boom tip position \(p_{tip}\). We solve this problem by adding an extra target onto the end of the transfer joint axle (B in Figure 1). However, using two targets adds ambiguity to the system because the crane can be driven into a posture where both targets are at an equivalent distance from the laser scanner. In this case, the targets are indistinguishable from each other when they are detected from the data. Additionally, the possibility of obstacles in the field of view of the scanner complicates the task as there is a risk of false positive detections.

Since the laser scanner is mounted onto the crane after the first joint (i.e., the slew joint) and since this joint is straightforwardly measured with an angle sensor, the following equations derived from Equation 2 are simplified by using a \(\rho-z\) plane which is aligned vertically along the boom so that the \(z\) axis is placed coaxial with the slew joint and the origin is placed at the slew joint. The \(\rho-z\) plane is spanned by the 2D laser scanner, and together they rotate about the slew angle so that \(\rho\) denotes a horizontal axis from the origin toward the boom tip. Positions of Target 1 \((p_{1}\)) and Target 2 \((p_{2}\)) have the following equations on that \(\rho-z\) plane:

\[
p_{1} = \begin{bmatrix} \rho_{1} \\ z_{1} \end{bmatrix} = \begin{bmatrix} a_{2} + a_{3}\cos(\theta_{2}) \\ d_{1} + a_{3}\sin(\theta_{2}) \end{bmatrix}.
\]

\[
p_{2} = \begin{bmatrix} \rho_{2} \\ z_{2} \end{bmatrix} = p_{1} + \begin{bmatrix} \Delta\rho \\ \Delta z \end{bmatrix} = p_{1} + \begin{bmatrix} a_{4}\cos(\theta_{2} + \theta_{3}) - d_{4}\sin(\theta_{2} + \theta_{3}) \\ a_{4}\sin(\theta_{2} + \theta_{3}) + d_{4}\cos(\theta_{2} + \theta_{3}) \end{bmatrix}.
\]

The laser scanner data consists of single scans,

\[
y(k) = \begin{bmatrix} r_{1} \\ \phi_{1} \\ r_{2} \\ \phi_{2} \\ \vdots \\ r_{N_{l}} \\ \phi_{N_{l}} \end{bmatrix},
\]

that contain \(N_{l} = 721\) range measurements each. The measuring angles are obtained from multiplying the receiver channel index with an angular constant of \(\Delta\phi\), which is the laser scanner resolution \((0.25^\circ)\). For each range \((r)\) and angle \((\phi)\) in the laser scanner coordinates, a position in \(\rho-z\) coordinates is

\[
p_{z} = \begin{bmatrix} \rho_{z} \\ z_{z} \end{bmatrix} = \begin{bmatrix} \rho_{z0} + r\sin(\phi + \phi_{z0}) \\ z_{z0} - r\cos(\phi + \phi_{z0}) \end{bmatrix},
\]

where \(\rho_{z0}\) and \(z_{z0}\) define the position of the laser scanner and \(\phi_{z0}\) is the rotation offset of the scanner. Together they form the pose of the scanner. Equation 5 assumes that the scanner starts collecting data from the downward direction (negative \(z\) axis in \(\rho-z\) coordinates) and ends its sweep toward the upward direction. The rotation offset parameter is required as the alignment of the scanner in the boom is not perfect after installation. (See Table 6 for estimated parameter values.)

3.3 Method SD: Simple target detector

In this method, the crane posture measurement is based on calculating the inverse kinematic solution of the crane model based on the two detected targets that are positioned and labeled. First, the method searches candidates for the two targets (shown in B and C in Figure 1) from the laser scan. The best crane joint configuration is then selected so that candidates match the targets mounted on the crane boom. The method is designed to work accurately only in easy cases without obstructions in the laser scanner data. This method is later used to initialize the proposed particle filter (see Section 3.4) and to calibrate the system setup (see Section 4.2).

### TABLE 2

| Denavit–Hartenberg parameters of the crane model and their ranges (from Kalmari et al., 2014) |
|---|---|---|---|---|
| \(i\) | \(a_{i}\) | \(d_{i}\) | \(\theta_{i}\) | Joint | \(\min\) | \(\max\) |
| 1 | 0 | 0 | \(\theta_{1}\) | \(\theta_{1}\) | \(-92^\circ\) | \(92^\circ\) |
| 2 | 90 | 0.09 | 0 | \(\theta_{2}\) | \(\theta_{2}\) | \(-29^\circ\) | \(82^\circ\) |
| 3 | 0 | 2.99 | 0 | \(\theta_{3}\) | \(\theta_{3}\) | \(-270^\circ\) | \(-94^\circ\) |
| 4 | -90 | -0.24 | \(d_{4}\) | 0 | \(\theta_{4}\) | 2.2 m | 5.6 m |

### TABLE 1

Fixed parameters for the joint angle calculation in Equation 1 (from Kalmari, 2015)

<table>
<thead>
<tr>
<th>Length (mm)</th>
<th>Angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>(l_{1})</td>
<td>(l_{2})</td>
</tr>
<tr>
<td>1175.1</td>
<td>346.0</td>
</tr>
</tbody>
</table>
An example of the point classification and the candidate positioning methods in $\rho$–$z$ plane, where there are two targets and two distracting objects among candidates. Closeups of targets are shown in their own subplots in the middle of the figure. A wire-frame model of the crane with reference target positions (blue circles) are drawn below laser scanner measurements and their classifications. Only middle points and edges associated with the found candidates are drawn. The light orange shadow visualizes the scanned area.

The candidate search part is derived from predecessors that were designed for tree detection and trunk diameter estimation for a horizontally aligned 2D laser scanner (Jutila, Kannas, & Visala, 2007; Ringdahl, Hohnloser, Hellström, Holmgren, & Lindroos, 2013). To detect the targets, that is, circular objects, we consider a given single 2D scan. The scanner sees far, unless there is an object blocking a part of the field of view. Using this knowledge, the range measurements of a single scan, which are indexed by their angular order (at interval of 0.25°), are classified into different clusters. The classification is done by comparing the differences of adjacent range measurements against a coefficient $C_e = 0.2$ m that is roughly an order of magnitude higher than the range measurement accuracy of the scanner. We label the measurements which are closer to each other than $C_e$ as middle points and cluster them for later use (e.g., required in Section 3.4.2). Then we search for left edges and right edges so that the range difference $> C_e$ and $< -C_e$, respectively. The edge point label is given for the point that has the shorter range when the range difference between the two adjacent points is larger than the threshold.

After classification, each range measurement is labeled either as a left edge, a middle point, a right edge, or an unclassified point. We require that candidates for the two targets must consist of a right and a left edge (in the right order) and possibly a group of middle points between them (see Figure 2). A candidate without any middle points can be accepted, but then the object consists of only two points, adjacent left and right edges. In this case, these left and right edge points are associated with the set of middle points for the later computation.

The proposed classification step is efficient in computing, and it effectively removes those false positives that would be caused by any single—likely noise originated—short-range measurement. The limitations of this method are twofold. First, it will not detect the object if the target object is even partly occluded by another object as the method requires left and right edges with a smooth area between them. Second, the method will only detect objects that cover a larger angle of view than 0.5° as smaller objects would not have separate left and right edges nor any middle points between them.

Next, the positions of the found candidates are estimated in the laser scanner coordinates. For each candidate, the angle ($\phi$) and the range ($r$) are computed by fitting a target-sized circle with a radius of $a = 30$ mm from the middle points associated with that candidate:

$$\phi = \frac{1}{N_m} \sum_{j=n_l}^{n_r} \phi_j,$$

$$r = \frac{1}{N_m} \sum_{j=n_l}^{n_r} \left( x_j + \sqrt{\max(0,a^2-y_j^2)} \right),$$

where

$$x_j = \cos(\phi_j - \phi) r_j, \quad y_j = \sin(\phi_j - \phi) r_j.$$

In Equation 6, $n_l$ is the index of that “middle point” that is nearest to the right edge, $n_r$ is the index of that “middle point” that is nearest to the left edge, $N_m = n_r - n_l + 1$ is the amount of middle points associated with the candidate, and $\phi_j$ is the angle of a range measurement ($r_j$). The max function in Equation 6b is used to handle candidates that have too many associated middle points in them to fit a circle with a radius of $a$ ($y_j^2 > a^2$) because otherwise the contents of the square
root would become negative. To illustrate the method, an example of range measurement clustering and candidate positioning is shown in Figure 2.

Next, the diameter of the candidate is measured to filter out too small and too large candidates. We used the edge-adjusted method for diameter estimation based on the viewing angle (VAEA method from Ringdahl et al., 2013), where diameter

\[ d = ((N - 1) \Delta \beta - 2a) r. \]  

In Equation 7, \( N \) is the amount of associated points (including edges) in that candidate, \( \Delta \beta \) is the laser scanner resolution (0.25°), \( a \) is the effective beam width (0.15°, the best value found for VAEA in Ringdahl et al., 2013) and \( r \) is the previously calculated range to the candidate. We decided to use 4 cm as a decision limit for discarding too large and too small candidates based on the difference between the diameter measurement and the target diameter of 2a. The 4-cm limit was chosen because the angular resolution of the laser scanner is equivalent to 4 cm at the maximum reach of the crane (≈8.5 m).

The remaining candidates are associated with the two scan targets on the crane boom by using Equations 3 and 5. As described previously, these two scan targets are indistinguishable from each other within a laser scan. Matching the candidates to the first target is statistically more likely to succeed than matching them to the second one, since there is only one rotational joint between the first target and the laser scanner. In addition, in the \( \rho-z \) plane, the accepted area of the two later joints is also dependent on the position of the first target. This is why all candidates are first tried whether they match with the first target.

The position of Target 1 determines the angle between the pillar and the lift joint. The corresponding joint angle \( \theta_2 \) is estimated by using the following procedure: The distance between the lift joint (lift in Figure 1) and Target 1 (B in the same figure) is known a priori (\( \theta_2 \) in Table 2) so we discard all Target 1 candidates which are \( \pm 5 \) cm apart from this. In computational detail, we perform a transformation so that the origin is translated to the lift joint position and candidates are discarded according to their range measures in polar coordinates. In addition, candidates with overly small or overly large joint angles are discarded (for physical limits, see Table 2).

In most cases, there is only one candidate left for the first target at this point. However, there is a finite probability that some of the wrong candidates fit into these constraints. On the one hand, this is handled by selecting the nearest matching candidate to the previous successful (lift joint) estimate. On the other hand, if there are no matching candidates left after discarding, then the crane posture estimation fails.

Matching the second target is somewhat more complex than matching the first one, as valid configurations depend on the position of the first target, and in addition, there are two unknowns to be determined: one rotational angle and the extension length (see Figure 1). This means that the search space for the second target is substantially larger than for the first one. Therefore, there are usually multiple matching candidates, for example, if there are obstacles in the field of view of the laser scanner. The transfer joint angle \( \theta_3 \) and the extension length \( d_4 \) can be derived from Equation 3 and Equation 5 using differences between the measured positions of the first target and the candidate for the second target, namely

\[
d_4 = \sqrt{\Delta \rho^2 + \Delta z^2 - a_4^2}.
\]

\[
\theta_3 = \arctan2\left( a_4 \Delta z - d_4 \Delta \rho, a_4 \Delta \rho + d_4 \Delta z \right) - \theta_2.
\]

where \( \Delta \rho \) and \( \Delta z \) are differences in \( \rho-z \) coordinates between the candidate and the first target (cf. Equation 3b). In Equation 8, \( a_4 \) is a constant parameter obtained from Table 2 and \( \theta_2 \) is the previously estimated angle of the lift joint.

Finally, an elimination step follows. Those candidates are discarded for which the values of \( d_4 \) or \( \theta_3 \) are outside of the accepted range (see Table 2). Note that as the accepted range of \( \theta_3 \) is partly outside the output range of the \( \arctan2 \) function in Equation 8b (i.e., they are on a different cycle), the computed value of \( \theta_3 \) has to be treated accordingly. In this case, one full round (360°) was subtracted from \( \theta_3 \) when the value was larger than zero. In a similar way than before, if there are multiple candidates at this point, then the closest to the last successful estimate is selected. Otherwise, if there are no candidates left after discarding, then the crane posture estimation fails.

### 3.4 Method CPPF: Crane posture particle filter

The hydraulic system of our forest machine is digitally controlled (Kalmari et al., 2013b). Our second method incorporates these digital control signals, in addition to the laser scanner measurements. Thus, our hypothesis is that since it contains more information than the previously introduced Method SD, it should provide a more reliable estimate of the crane posture, especially when the line of sight to the scan targets is temporarily obstructed.

The posture of the crane cannot be uniquely defined using a laser scanner and two scan targets, as previously explained (see Section 3.3). Moreover, the interpretation of the measurement data is difficult also because the targets are indistinguishable from each other (see Section 3.3), and observations are likely to contain obstructions, occlusions, and noise. On the other hand, digital control signals consist of commands given to hydraulic servo valves (e.g., from operator’s joystick). These signals precede the movement of the crane, and additionally, the relationship between these signals and the crane movement is nonlinear (see Section 3.4.1). To combine these two sources of information, we intend to obtain an estimate of the crane posture by an inverse—probabilistic—approach. This can be done efficiently with a particle filter.

A particle filter estimates the states of a hidden Markov model in a sequential fashion (Arulampalam, Maskell, Gordon, & Clapp, 2002; Candy, 2007). After each given observation, the (hidden) state of the system is estimated from the posterior density of the state variables. We use a sampling importance resampling (SIR) type particle filter, first proposed by Gordon et al. (1993).1 In the SIR filter, a transition prior is used as the importance density in the weight update stage.

---

1 The filter type is also called bootstrap particle filter (Candy, 2007; Gordon, Salmond, & Smith, 1993) as the key update stage of the algorithm (Bayes rule) is implemented as a weighted bootstrap (Smith & Gelfand, 1992).
TABLE 3 Used parameters for the proposed CPPF algorithm

<table>
<thead>
<tr>
<th>$N_p$</th>
<th>$\sigma_{\theta_2}$</th>
<th>$\sigma_{\theta_3}$</th>
<th>$\sigma_{d_4}$</th>
<th>$\sigma_{de}$</th>
<th>$C_{init}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>0.5°/s</td>
<td>1.0°/s</td>
<td>0.075 m/s</td>
<td>0.03</td>
<td>0.35</td>
</tr>
</tbody>
</table>

(Arulampalam et al., 2002; Candy, 2007; Gordon et al., 1993). This leads to a major simplification of the particle filter as only the likelihood of the measurement $y(k)$, $\mathcal{L}(y(k)|x_i(k))$, is used to update weights $w_i(k) \in \mathbb{R}$ for each particle $x_i(k), i = 1, \ldots, N_p$ as follows:

$$w_i(k) = w_i(k - 1)\mathcal{L}(y(k)|x_i(k)). \quad (9)$$

The benefit of the SIR method is that the importance weights are simple to evaluate and the importance density can be easily sampled (Arulampalam et al., 2002). The disadvantage of this simplification is that since neither earlier nor current round measurements are taken into account at the prediction phase, the particles are depleted much faster than in the original sequential importance sampling algorithm (Arulampalam et al., 2002). This means that a few particles will eventually have a significantly large share of the total weight. This is called a degeneracy problem. To avoid it, a high concentration of probability mass at a few particles should be prevented by, for example, resampling (Arulampalam et al., 2002; Gustafsson et al., 2002).

Although resampling effectively deals with the degeneracy problem, it introduces a new problem, called the sample impoverishment problem. Because particles with large weights are likely to be drawn multiple times during resampling, whereas particles with minor weights are not likely to be drawn at all, the diversity of the particles will tend to decrease after the resampling step. This problem is severe in the case of a small process noise (Arulampalam et al., 2002). However, in our case, this is not a problem as the uncertainty of predicted velocities in Equation 10 is significantly large (see also parameter values in Table 3).

In our case, particles represent parametric states of the kinematic model of the forestry crane (of Section 3.1), namely $x_i(k) \in \mathbb{R}^3$ is the ith particle, $i = 1, \ldots, N_p$, sampling the 3D state space $S$ (two joint angles $\theta_2, \theta_3$, and the length of the extension, $d_4$) at time step $k$. The amount of particles $N_p = 1000$ (see Table 3). Note that $\theta_1$ is not incorporated in this model but is instead measured directly with an angle sensor. In our case, $y(k) \in \mathbb{R}^{721}$ contains the range measurements of one scan obtained at a time step $k$.

The algorithm has four phases; prediction, update, normalization, and resampling. The way we implement the SIR filter for the crane posture estimation is similar to Monte Carlo localization presented for robot pose estimation by Thrun et al. (2005, p. 252). However, we limit the state space $S$ as we know the limits of the joints of our crane. In other words, we define predicted weight $w_i(k)$, which is set to zero instead of the previous weight if the particle has been moved to a no-go zone (see Equation 12).

We use the kinematic model of the crane and our model of the hydraulics with control signals in the prediction phase. The usage of noisy hydraulic signals as control inputs insert a level of noise to the predictions that substantially alleviates the degeneracy problem which arises from resampling. Thus we can safely resample our particle filter at each iteration. This is reasonable since we have large process noise in the prediction step to overcome uncertainties of the hydraulic control model. In other words, our particles deplete fast and this is overcome with resampling at every iteration.

The estimate for the crane posture is obtained from the particle closest to the center of the largest concentration of probability mass at each iteration. This is obtained by using a kernel density estimate with Gaussian kernels. The kernel density estimate could have been used to modify the method into a regularized particle filter (Musso, Oudjane, & Le Gland, 2001), but we decided to keep the filter simple, as the modification would have increased the computational cost because new particles would then have had to be sampled from a continuous probability distribution.

We call our implementation of the SIR filter for the crane posture estimation as crane posture particle filter (CPPF). The algorithm has the following phases (see also Figure 3):

0. **Initialization**, where particles are uniformly distributed around the state space. All the weights $w_i$ are initialized to an equal weight of $1/N_p$. In addition to this default initialization procedure, we change one particle to match each of the crane posture hypotheses calculated from target candidates found with Method SD (see Section 3.3) to speed up the initialization phase so that one particle is initially placed to each found posture hypothesis.

1. **Prediction**, where the dynamic model of the crane and the controls of hydraulic valves are used to predict the crane posture and add noise to the system for each $i = 1, \ldots, N_p$ by drawing predicted particles from a normal distribution,

$$\hat{x}_i(k) \sim \mathcal{N}(x_i(k - 1) + I_i w_i(k) \Delta t_i(k), \Sigma). \quad (10a)$$

where

$$I_i = \text{diag}(I_{i,1}, I_{i,2}, I_{i,3}).$$

$$I_{i,s} = \begin{cases} 1, & U < 0.9, \quad U \sim U(0, 1) \\ 0, & \text{otherwise} \end{cases} \quad \forall s \in \{1, 2, 3\}. \quad (10b)$$

In Equation 10, $x_i(k)$ is again the ith particle in a 3D state space $S$ (two joint angles $\theta_2, \theta_3$, and the extension length, $d_4$) at time step $k$. $I_i$ is a random indicator function to drop a velocity measurement of a state to zero for 10% of randomly selected particles for each state $s$ independently. It is implemented in Equation 10b by sampling a standard uniform distribution ($U(0, 1)$) for each $i$ and $s$. This modifies the distribution to have two modes for each state: the first (90% of the probability mass) at the predicted position, and the other (10%) at the previous position with the same standard deviation. This modification is required to handle situations taking

FIGURE 3 Overview of the proposed CPPF algorithm
place now and then, when control signals indicate a movement, but the crane does not move accordingly. These kinds of events may be caused, for example, by the joint limits, or by (unknown) obstacles that restrict the movement of the crane.

In Equation 10a, \( \hat{x}_i(k) \) is the predicted particle value, which is sampled from a normal distribution for each state independently. In the equation, the mean of the normal distribution is located at the previous state \( x_i(k-1) \), which is updated by adding the movement predicted with the velocity \( v(k) \), which is predicted using control signals of the hydraulic valves and the nonlinear model defined in Section 3.4.1, and a sample period \( \Delta t(k) \) (a period between the indices \( k - 1 \) and \( k \)).

As the states are assumed independent of each other, the covariance matrix,

\[
\Sigma = (\Delta t(k))^2 \text{diag} \left( \sigma_\theta_2^2, \sigma_\theta_3^2, \sigma_d^2 \right),
\]

is defined to have variances on the main diagonal and zeros elsewhere. These variances are constructed from the sample period \( \Delta t(k) \) and standard deviations of velocity errors for each state: \( \sigma_\theta_2 \), \( \sigma_\theta_3 \), and \( \sigma_d \). These variances were estimated by comparing reference measurements with model-predicted velocities in a separate data set used to identify the prediction model of hydraulics defined in Section 3.4.1 (see Table 3 for values).

At the end of each prediction step, invalid state configurations are detected and their corresponding weights are set to zero. For this purpose, we define a subset of feasible states \( S_i \subset S \), where \( \theta_2 \in [\theta_{2,\text{min}}, \theta_{2,\text{max}}] \), \( \theta_3 \in [\theta_{3,\text{min}}, \theta_{3,\text{max}}] \), and \( d_4 \in [d_{4,\text{min}}, d_{4,\text{max}}] \) (see Table 3 for used values). Then we introduce a predicted weight:

\[
\hat{w}_i(k) = \begin{cases} 
   w_i(k-1), & \text{if } \hat{x}_i(k) \in S_i \\
   0, & \text{otherwise.}
\end{cases}
\]

2. **Update**, where weights \( w_i(k) \in \mathbb{R} \) are updated from given observations \( y(k) \in \mathbb{R}^{21} \) conditioned on the predicted states \( \hat{x}_i(k) \in \mathbb{R}^3 \). These are obtained from measurement likelihoods as

\[
w_i(k) = \hat{w}_i(k)|L(y(k)|\hat{x}_i(k)).
\]

The derivation of the measurement likelihood \( L(y(k)|\hat{x}_i(k)) \) is presented later in Section 3.4.2.

3. **Normalization**, where each unnormalized weight \( w_i(k) \) is divided with the sum of all updated weights to get the normalized weight

\[
\mathcal{W}_i(k) = \frac{w_i(k)}{\sum_{i=1}^{N_p} w_i(k)}.
\]

4. **Resampling**, where a new set of particles \( x_i(k) \) are drawn among the predicted particles \( \hat{x}_i(k) \) according to the normalized weights \( \mathcal{W}_i(k) \). This can be efficiently done using an inverse transform sampling method (Arunlampalam et al., 2002). After resampling, all weights \( w_i(k) \) are set to a value of \( 1/N_p \).

After the fourth phase, the first phase is reentered (see Figure 3) for the next time step. The best crane posture estimate is computed from the set of all particles after the normalization phase. A kernel density estimate with Gaussian kernels (Musso et al., 2001) is used to find the particle closest to the center of the probability mass of nearby particles. Specifically, the kernel density estimate \( D_i(k) \) is computed for each particle at time step \( k \) using an equation

\[
D_i(k) = \sum_{j=1}^{N_p} \mathcal{W}_j(k) e^{-\frac{(\|x_i(k) - x_j(k)\|)^2}{\sigma_{\text{scale}}}},
\]

where \( \mathcal{W}_j(k) \) is a normalized weight and \( x_i(k) \) is the corresponding \( i \)-th particle. In the equation, \( \sigma_{\text{scale}} \) is the variance of the kernels in the density estimate. The used \( \sigma_{\text{scale}} \) value was 0.03 (see Table 3), which is about 1.7° for first two angular states and 3 cm for the extension. For simplicity, we used the same kernel size parameter for each of the three states as the probability distributions were roughly similar in each dimension. Finally, a maximum a posteriori (MAP) estimate is used to select the particle that has the largest kernel density estimate, \( D_i(k) \) in Equation 15. The state represented by this particle is taken to be the best crane posture estimate.

The value of the MAP estimate,

\[
\hat{D}(k) = \max_{i=1\ldots N_p} D_i(k),
\]

is limited between zero and one, and it approaches to one when all particles are at the same place. When all particles are dispersed, then the value approaches to zero. The benefit of the MAP estimate value is twofold. In a relative sense, the largest value gives the particle closest to the center of a cluster yielding a best estimate for the target position. In an absolute sense, it acts as a quality self-measure to distinguish between unreliable (\( \hat{D} \sim 0 \)) and reliable (\( \hat{D} \sim 1 \)) detections. If this value drops below the threshold \( C_{\text{init}} = 0.35 \), a reinitialization is made. Apart from this reinitialization threshold, we use the value of 0.5 for classification purposes to label results as good or poor (see the Results section).

The reinitialization is similar to the initialization step, except that the particles are not redistributed uniformly. The previous low-quality estimate is just enhanced with the crane posture hypotheses calculated from target candidates found with Method SD described in Section 3.3.

### 3.4.1 Crane joint velocities for the prediction phase of CPPF

The crane joint velocities \( v(k) \) (two angular velocities \( \dot{\theta}_2 \) and \( \dot{\theta}_3 \), and a linear velocity \( \dot{d}_4 \) at time step \( k \)) in Equation 10 are predicted by first reading control signals from a vehicle bus in the prototype forest machine (Kalmari et al., 2013b) and then by using a modeled relationship between the given controls and the realized velocities of the crane. This model has two parts. In the first part, velocities of hydraulic cylinders induced by control signals are predicted using a four parameter nonlinear model and a time delay (from Kalmari et al., 2014). The model...
between a given control $u_i$ and a velocity of a hydraulic cylinder $d_i$ for each cylinder $c = 1, \ldots, 4$ is

$$d_i(k) = \begin{cases} K_c (u_i(k - \Delta k_i) - D_c), & u_i(k - \Delta k_i) < D_c, \\ 0, & D_c \leq u_i(k - \Delta k_i) \leq D_c, \\ K_c (u_i(k - \Delta k_i) - D_c), & u_i(k - \Delta k_i) > D_c, \end{cases} \quad (17)$$

where $K_c$ is the gain and $D_c$ is the dead zone on the negative side, and $K_c$ and $D_c$ on the positive side, respectively. (This function is later visualized with a black line in Figure 9.) The time delay is handled by using $\Delta k_i$ time steps older control signals, where $\Delta k_i$ is identified with a separate correlation test over time steps $k$ for each cylinder $c = 1, \ldots, 4$ separately. The parameters $K_c$, $D_c$, $K_c$, $D_c$, and $\Delta k_i$ are calibrated in Section 4.3 for each cylinder $c$, except the first one which can be omitted as the corresponding joint angle is directly measured in the proposed setup.

In the second part, the cylinder velocities ($d = [d_1, d_2, d_3, d_4]^T$) are transformed to angular velocities of the crane joints. These can be analytically derived from the model in Equation 1. First, we define inverses of Equations 1a and 1b with cylinder lengths $d_2$ and $d_3$ from the estimated joint angles $\theta_2$ and $\theta_3$, respectively:

$$d_2 = \sqrt{\frac{l_2^2 + l_2^2}{1 - \cos(\gamma_2)}},$$

$$d_3 = \sqrt{\frac{l_2^2 + l_2^2}{1 - \cos(\gamma_3)}},$$

where

$$\gamma_2 = \arcsin \left( \frac{l_7}{l_9} \sin(\theta_{2b} - \theta_3) \right) + \arccos \left( \frac{l_7^2 + l_9^2 - l_7^2}{2l_9 l_7} \right),$$

$$l_9 = \sqrt{l_5^2 + l_2^2 - 2l_2 l_7 \cos(\theta_{2b} - \theta_3)}. \quad (18c)$$

Then we derive angular velocities $\dot{\theta}_2$ and $\dot{\theta}_3$ by differentiating Equations 1a and 1b with cylinder lengths $d_2$ and $d_3$ and multiplying these results with cylinder velocities $d_2$ and $d_3$, respectively:

$$\dot{\theta}_2 = \frac{d_2}{l_2^2 \sqrt{1 - \cos(\gamma_2)}},$$

$$\dot{\theta}_3 = \frac{d_3 l_2 \sin(\gamma_2)}{l_7 l_9 \sin(\gamma_3 - \gamma_2)} \left( \frac{\cos(\gamma_3) - \frac{l_7^2}{l_7^2}}{\sqrt{1 - \cos(\gamma_3)^2}} + \frac{\cos(\gamma_3) - \frac{l_7^2}{l_7^2}}{\sqrt{1 - \cos(\gamma_3)^2}} \right),$$

$$\quad \text{where} \quad \cos(\gamma_1) = \frac{l_7^2 + l_7^2 - l_7^2}{2l_1 l_2}, \quad \cos(\gamma_2) = \frac{l_7^2 + l_7^2 - l_7^2}{2l_2 l_7},$$

$$l_6 = \sqrt{l_5^2 + l_5^2 - 2l_5 l_5 \cos(\gamma_3)}. \quad (19c)$$

Since the extension velocity $d_4$ was already estimated in the first part, we can form a vector of crane joint velocities $v$ (two angular velocities $\dot{\theta}_2$ and $\dot{\theta}_3$, and a linear velocity $d_4$) used as a control input in the proposed CPPF (in Section 3.4). In Equations 18 and 19, $d_2$ is length of the lift cylinder and $d_3$ is length of the transfer cylinder. All other lengths $l_1, l_2, l_3, l_4, l_5, l_7$, and $l_6$, and angles $\theta_{2b}, \theta_{3b}$, and $\gamma_{23}$ are constant parameters defined by Kalmari (2015) and their values are presented in Table 1.

### 3.4.2 Likelihoods of laser scanner measurements for the update phase of CPPF

In this section, we demonstrate the calculation of the likelihood of laser scanner measurements of Equation 13 which is required in the update phase of the proposed CPPF algorithm. The likelihood $L(y(k)|x(i_k))$ is calculated for a scan $y(k) \in \mathbb{R}^{721}$ of Equation 4 given the ith particle $x(i_k) \in \mathbb{R}^3$ at time step $k$. For brevity, however, the index $k$ is later omitted in this section.

Each particle $x_i$ represents a single hypothetical crane posture, which determines the locations of the two targets. Thus, positions of the two expected targets are different for each $i$. To compare them with the laser range observations, the positions of all expected targets are first transformed into the laser scanner coordinates (i.e., a range $r_{ij}$ and an angle $\phi_{ij}$) for each $i = 1, \ldots, N_p$ and target $j \in \{1, 2\}$ by using the inverse of Equation 5:

$$s_{ij} = \begin{bmatrix} r_{ij} \\ \phi_{ij} \end{bmatrix} = \begin{bmatrix} \sqrt{(\rho_{ij} - \rho_{i0})^2 + (z_{ij} - z_{i0})^2} \\ \arctan2(\rho_{ij} - \rho_{i0}, z_{i0} - z_{i0}) \end{bmatrix},$$

where, the $\rho$-$z$ plane coordinates $\rho_{ij}$ and $z_{ij}$ are calculated from the states of particles $x_i$ by using Equation 3.

We want the likelihood estimation to be performed in real time with limited computational resources. To achieve this, we invert the problem to a task of measuring how well each pair of expected targets fits with the laser scan by using an inverse measurement model instead of the (forward) model conventionally used with particle filters. The computational benefit comes from a fact that there are only two small identical targets but 721 laser range observations in each scan. Through the inversion, we avoid ray-casting of all laser range observations to a surface defined by the two targets for each particle. The inversion can be done probabilistically using the Bayes rule:

$$L(y|x_i) \propto P(y|x_i) = \frac{P(x_i|y) P(y)}{P(x_i)}.$$

Here, the inverse measurement model $P(x_i|y)$ for each $i = 1, \ldots, N_p$ given the measurement $y$ is multiplied with the probability of the laser scan $P(y)$ and divided by the probability of the ith particle $P(x_i)$.

Next, we make two assumptions. The first one is that $P(x_i)$ is constant for all $i$. This assumption is reasonable, because particles are resampled at the end of each iteration of CPPF algorithm, and therefore the probability of each particle $P(x_i)$ is equal for all $i = 1, \ldots, N_p$.

The second assumption is that $P(y)$ stays constant on the area of interest, $r \in [0, 10]$ m and $\phi \in [0^\circ, 180^\circ]$. It is justifiable because laser scanners are usually built to detect objects as equally as possible within their measurement range on the scanned area. In our case, that area covers all possible locations of both targets. Thus, in Equation 21, $P(y)$ and $P(x_i)$ are unknown constants and we can assume that

$$L(y|x_i) \propto P(x_i|y).$$

(22)
Finally, since the weights of the particles are normalized in the normalization phase of the CPPF method, the remaining unknown but constant scale factor between the likelihood of a scan \( L(y|x_i) \) and the inverse measurement model \( P(x_i|y) \) does not affect the rest of the procedure in the method.

To estimate the inverse measurement model efficiently, we make an approximation and assume that we can model the fitness of each target to the scan separately by only considering that single range observation that matches with the position of an expected target. To compute a joint probability for both targets, we assume that the fitness values do not interfere with each other and are independent. Thus, we can simply multiply together the two separately computed fitness values of targets. In detail, the inverse measurement model can be expressed as

\[
P(x_i|y) \approx \prod_{j=1}^{N_l} \delta_{ij} L(r_{ij}|r_i),
\]

where

\[
\delta_{ij} = \begin{cases} 1, & \text{when } |\phi_i - \phi_j| < \Delta \beta/2 \\ 0, & \text{otherwise}. \end{cases}
\]

In Equation 23, \( \delta_{ij} \) is defined as equal to one only when the angles of a laser range observation (\( \phi_i \)) and an expected target (\( \phi_j \)) match within the laser scanner resolution (\( \Delta \beta \)). For a scan, this happens for a single configuration of indexes \( i \) and \( j \), for both targets if targets are on the field of view of the scanner. Thus only one matching range measurement is compared with each target \( j \in T = \{t1, t2\} \) using a one-dimensional fitness function \( L(r_{ij}|r_i) \).

Unfortunately, this approximation adds a source of error because the neighboring laser range measurements are not checked when deciding if the expected target fits to the measurement or not. For this reason, we have enhanced the method to take neighboring measurements into account by using a precomputed cluster-size and a middle-of-a-cluster measure. They are computed for each laser range measurement after the scan is formed. They can be computed as by-products of Method SD (see Section 3.3).

The proposed fitness function \( L(r_{ij}|r_i) \), which is our approximation of the likelihood of a range of an expected target \( r_{ij} \) given the matched laser range observation \( r_i \) (including the precomputed measures \( M_l \) and \( m_l \)), is defined as

\[
L(r_{ij}|r_i) = \begin{cases} L_{\text{miss}}, & d_{ij} > \epsilon_d \\ l_{\text{step}} + (1 - l_{\text{step}}) L_{\text{target}}(r_{ij}; r_i, M_l, m_l), & d_{ij} \leq \epsilon_d \end{cases},
\]

where

\[
d_{ij} = r_i + a - r_{ij}.
\]

In Equation 24, \( r_i \) is the laser range measurement, \( r_{ij} \) is the range of the expected target, and \( d_{ij} \) is the distance between the expected target and the target indicated by the range measurement \( r_i + a \). The fitness function is constructed from a step function which increases the likelihood of an expected target to \( l_{\text{step}} \) after the target can be fitted behind the range measurement (with a safe margin \( \epsilon_d \)).

Before the step, the target is closer to the scanner than the range observation would indicate. There, we define a likelihood of missing the expected target. It is defined to increase as a function of range because targets appear linearly smaller at larger ranges, and thus they are more likely to be seen through. Note that the constant value of the parameter \( l_{\text{miss}} \) should be small enough (see Table 4 for parameter values). After the step, when the target is behind the range observation, the fitness is modeled as a function of a constant value \( l_{\text{step}} \) and a target-likeness measure \( L_{\text{target}}(r_{ij}; r_i, M_l, m_l) \). The latter is a function of the expected range \( r_{ij} \), the observed range \( r_i \), the precomputed cluster-size measure \( M_l \), and the precomputed middle-of-a-cluster measure \( m_l \).

An example of the one-dimensional fitness function in Equation 24 is shown in Figure 4.

The target-likeness measure \( L_{\text{target}} \) in Equation 24a is constructed with the help of three Gaussian functions:

\[
L_{\text{target}}(r_{ij}; r_i, M_l, m_l) = L_{\text{dist}}(d_{ij}) L_{\text{size}}(M_l, r_{ij}) L_{\text{mid}}(m_l, r_{ij}),
\]

where

\[
L_{\text{dist}}(d_{ij}) = e^{-d_{ij}^2/\sigma_{\text{dist}}^2},
L_{\text{size}}(M_l, r_{ij}) = e^{-|M_l - r_{ij}|^2/\sigma_{\text{size}}^2},
L_{\text{mid}}(m_l, r_{ij}) = e^{-|m_l - r_{ij}|^2/\sigma_{\text{mid}}^2}.
\]

In Equation 25, \( d_{ij} \) is the difference defined in Equation 24b, \( r_{ij} \) is the range of the expected target, \( \Delta \beta \) is the angular resolution of the laser scanner, \( M_l \) is the precomputed cluster-size measure, in detail, the amount of middle points associated with a cluster in Method SD (see Section 3.3), and \( m_l \) is the precomputed middle-of-a-cluster measure. It is computed as a count from the current index \( i \) to the center of the current cluster of middle points.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Reasonable range</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \beta )</td>
<td>0.25°</td>
<td></td>
<td>Angular resolution of the scanner</td>
</tr>
<tr>
<td>( a )</td>
<td>30 mm</td>
<td></td>
<td>The radius of an expected target</td>
</tr>
<tr>
<td>( \epsilon_d )</td>
<td>50 mm</td>
<td>( a … 2a )</td>
<td>The safe margin for detection</td>
</tr>
<tr>
<td>( \sigma_{\text{dist}} )</td>
<td>50 mm</td>
<td>( a … 2a )</td>
<td>Weights the right distance behind the range measurement</td>
</tr>
<tr>
<td>( \sigma_{\text{size}} )</td>
<td>400 mm</td>
<td>10a … 20a</td>
<td>Weights the size of clustered range measurements</td>
</tr>
<tr>
<td>( \sigma_{\text{mid}} )</td>
<td>30 mm</td>
<td>( a … 2a )</td>
<td>Weights the center of clustered range measurements</td>
</tr>
<tr>
<td>( l_{\text{step}} )</td>
<td>0.5</td>
<td>0.4 … 0.6</td>
<td>The likelihood of the target in unseen (unknown) area</td>
</tr>
<tr>
<td>( l_{\text{miss}} )</td>
<td>0.01</td>
<td>(&lt; l_{\text{step}}/\text{max range})</td>
<td>The likelihood of missing a target</td>
</tr>
</tbody>
</table>
The first Gaussian function \( L_{\text{dist}} \) in Equation 25b weights the right distance behind the range measurement to fit a target. Its parameter \( \sigma_{\text{dist}} \) should be near the radius of the expected target. The second one \( L_{\text{size}} \) in Equation 25c weights small clusters and discards too large clusters. Its parameter \( \sigma_{\text{size}} \) should be tuned to large enough not to filter target-size clusters. The last one \( L_{\text{mid}} \) in Equation 25d then weights the locations at the centers of clusters. Its parameter \( \sigma_{\text{mid}} \) should also be near the radius of the target. This last one is a heuristic which is added to keep the area of the likely locations of targets similar in small and large clusters of range observations. It is based on an idea that on target-sized clusters, the target most likely is located at the center. When all these functions together have their value near 1, the value of the fitness function \( L(r_{i,j}|r_l) \) in Equation 24 has the largest value. Note that each Gaussian function can have values between 0 and 1 since they are not normalized.

The proposed fitness function in Equation 24 was crafted to approximate the 2D shape of the underlying likelihood of an expected target in the \( \rho-z \) plane, but on the same time, we required it to be efficiently computed. In the function, the constant part allows a similar response of the filter to the occlusion anywhere on the line of sight between the scanner and the target. The value of \( l_{\text{step}} \) can be understood as a likelihood of the target in an unknown or occluded location. The Gaussian parts in the target-likeness measure \( L_{\text{target}} \) together shape the likely location just behind the frontier of range observations. The parameters are tuned to shape the likely hot spot to match the physical size of the expected target (radius of \( a \)) in the \( \rho-z \) coordinates (see Table 4 for more details). To show how our approximation predicts target-shaped objects from the given laser scan, the function is computed for all possible target locations in the \( \rho-z \) plane given an example scan in Figure 5.

### 3.5 Gravity-dependent reference for the crane posture

It is challenging to obtain an accurate reference for the posture of the forestry crane in a natural outdoor environment with obstacles and foliage, as mentioned in Introduction. We decided to use the...
instrumentation of the forestry crane built in our previous research (Kalmari et al., 2013b) as a reference even though it did have some limitations. Our crane was instrumented using a magnetic linear encoder strip on the slew joint, magnetostrictive linear position sensors attached to hydraulic cylinders on the lift and the transfer joints, and a wire draw encoder for the prismatic joint on the telescopic extension boom. The pose of the targets could be estimated accurately using the kinematic model of the crane in Equation 3, if the crane boom would not bend. It does bend however and does so by quite an amount even when used without any external load. For example, the misplacement induced by gravity on the position of the boom tip is larger than 0.1 m when the boom is fully extended without external load (see the shadow in Figure 6). Obviously, this deformation has to be taken into account to obtain a reference posture to measure the accuracy of our proposed SD and CPPF methods.

Our solution for dealing with the crane flexibility and gravitational effects was to concentrate on estimating the reference positions of the scan targets with a sufficient accuracy. We used a finite segment method by Huston (1981) to model the bending of the boom in gravity because it is intuitive and it has got fairly good results in the previous research with hydraulic cranes (e.g., Bak & Hansen, 2013; Hansen, Andersen, & Conrad, 2001; Pedersen, Hansen, & Ballebye, 2010). In the method, the flexibility of boom is modeled as linear torsional springs between the different rigid segments (Pedersen et al., 2015). The main advantage of the method is that it is based on rigid body modeling techniques, making it easy to implement (Bak & Hansen, 2013). It can also effectively model the crane with only a few parameters as the prismatic joint (extension) can be approximated as a single extending segment (Pedersen et al., 2015).

The finite segment method needs the center of mass to be calculated for each segment. We divided the model to four segments: The first segment (pillar) is stationary in the \( p-z \) plane, the second segment (inner boom) consists of the boom between lift and transfer joints, the third segment (outer boom) has the telescopic extension, and the fourth segment is the tool hanging on the tip of the boom (see Figure 6).

![FIGURE 6](image.png) Bending of the crane in gravity using the finite segment method. The shadow at the background visualizes the posture of the boom in zero gravity. Also centers of mass and related parameters are shown

For this work, we only modeled the bending of the second and the third segments as the laser scanner was mounted on the top end of the first segment. This is because the bending or motion of the first segment does not affect our comparison between the reference and the laser observations.

The locations of center of mass in the \( p-z \) plane can be calculated using equations derived with the help of Equations 2 and 3,

\[
\begin{align*}
\mathbf{p}_{m_2} &= \begin{bmatrix} m_2z_2 \\ \rho_m \\ 0 \end{bmatrix} = \begin{bmatrix} a_2 + a_{m_2} \cos(\theta_2) - d_{m_2} \sin(\theta_2) \\ d_1 + a_{m_2} \sin(\theta_2) + d_{m_2} \cos(\theta_2) \end{bmatrix}, \\
\mathbf{p}_{m_3} &= \mathbf{p}_{m_2} + \begin{bmatrix} a_{m_3} \cos(\theta_2 + \theta_3) - d_{m_3} \sin(\theta_2 + \theta_3) \\ a_{m_3} \sin(\theta_2 + \theta_3) + d_{m_3} \cos(\theta_2 + \theta_3) \end{bmatrix},
\end{align*}
\]

where \( d_1 \) and \( a_2 \) are constant parameters defined in Table 2, \( \mathbf{p}_{m_1} \) is the position of the first target in Equation 3a, \( \theta_2 \) and \( \theta_3 \) are the joint angles, and \( a_{m_2}, d_{m_2}, a_{m_3}, \) and \( d_{m_3} \) are parameters indicating the center of mass locations (see Figure 6). As the third segment is changing shape, the parameter \( d_{m_3} \) is changed as a function of \( d_4 \) to compensate this effect. These parameters were obtained from manual adjustment using a computer-aided design (CAD) model of the crane provided by Kesla (see Table 5 for used parameter values\(^6\)).

We assumed that the motion of the crane is slow so that no dynamical effects, for example, vibrations, occur. Thus, the only significant force in the crane is the gravity of earth, which is assumed to point toward the negative \( z \) axis. This causes torque to joints so that masses \( m_{tool} \) and \( m_3 \) bend the assumed torsional spring in the transfer joint (\( \theta_3 \)) relative to their distance to the joint in the \( p \) axis. Similarly, all masses

\(^6\) Note that because of the used kinematic model, \( a_{m_2} \) and \( d_{m_2} \) are the larger values and that \( d_{m_3} \) is negative.

### Table 5: Parameters used in the bending compensation method

<table>
<thead>
<tr>
<th>i</th>
<th>( a_{m_i} )</th>
<th>( d_{m_i} )</th>
<th>( m_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.625 m</td>
<td>0.05 m</td>
<td>290 kg</td>
</tr>
<tr>
<td>3</td>
<td>-0.3 m</td>
<td>0.321d_4 + 0.069 m</td>
<td>350 kg</td>
</tr>
</tbody>
</table>
The optical axis (of the rotating mirror) of the laser scanner was placed 0.1 m above the floor. To this end, we detached the laser scanner from the crane and put it on the floor scanning horizontally on a plane 0.1 m above the floor. The pose of the scanner was measured manually in each of these test sequences. We measured six separate test sequences, where each had a different (manually rotated) orientation of the laser scanner. This is done to add noise to the orientation of the scanner to minimize the discretization effect caused by the limited angular resolution of the scanner (0.25°).

As we chose to calibrate the system setup by fitting together the positions of the model-predicted targets and the observed targets, we have to first measure the errors of our target detector method (introduced in Section 3.3) with an independent test setup. This choice is beneficial as it allows us to calibrate the scanner pose as a by-product of the reference measurement calibration in Section 4.2.

Finally at the end of this section, we outline the main tests that we shall make in the Results section to test the accuracy of the proposed methods.

### 4.1 Independent target positioning test

This test gives the target positioning accuracy of Method SD when candidates are unimpededly visible and correctly associated with right targets. To this end, we detached the laser scanner from the crane and put it on the floor scanning horizontally on a plane 0.1 m above the floor. The optical axis (of the rotating mirror) of the laser scanner was placed to a fixed point (the origin). We placed test points at 0.2 m intervals from 0.2 to 10 m in a straight line in front of the laser scanner (x axis in Figure 7).

In a test sequence, we placed the target sequentially to each of the test points and measured it for a few seconds with the laser scanner. We measured six separate test sequences, where each had a different (manually rotated) orientation of the laser scanner. This is done to add noise to the orientation of the scanner to minimize the discretization effect caused by the limited angular resolution of the scanner (0.25°).

The pose of the scanner was measured manually in each of these test sequences.

In each test sequence, all candidate position measurements obtained from Method SD (see Section 3.3) were captured when the target was at a test point. We rejected all measurements, when the target was moved between the test points. The tape measurements of the test points and the placements of the targets were done with an accuracy of a few millimeters. Concurrently, this is also the accuracy of this test and it is sufficient since the expected errors in the laser scanner measurements are about one magnitude larger. The used LMS 221
All measurements are combined with the reference positions. The topmost subplot shows the angular error in degrees, the middle plot shows the sideways error ($y$ axis), and the bottom plot shows the range error ($x$ axis) as a function of the reference range. The solid red line is the mean and the dashed lines are $3\sigma$ confidence intervals. Measurements (black dots) are plotted using a small Gaussian noise in their position to visualize the amount of measurements at the same point.

sensor has a typical range measurement accuracy of $\pm 35$ mm (SICK AG, 2006).

The results of the test are combined in Figure 8, which shows that the angular error is within $\pm 0.3^\circ$ almost all the time. The larger angular errors within the first meter are most probably caused by a small misplacement of the laser scanner in the test. Note that the limited angular resolution is visible in the middle of Figure 8 as the measurements are grouped to clusters on larger ranges. As the measurement errors in $x$ (along the line) and $y$ (perpendicular to the line) directions are small (less than $\pm 3$ cm) and as the measurement has nearly a zero mean at a range between 1.8 and 8 m, we conclude that the method can be relied upon when performing calibrations within that range. Specifically, this range interval is used with the calibration data set (Test A), which does not contain any false target detections with Method SD (see Figure 11).

4.2 | Reference for the crane posture

As stated, the reference measurement system (introduced in Section 3.5) has a number of parameter values that need to be calibrated before the system can be used. Since we are computing the reference in any case, we shall optimize its parameters and those for the laser scanner pose together in a single optimization. An alternative for field work purposes would be to calibrate just the pose of the scanner by, for example, driving the crane to a set of selected extreme postures.

There are multiple parameters that are estimated simultaneously. First, the joint angles of our crane are measured using position sensors attached to hydraulic cylinders and to the extension mechanism. The zero offset (bias) of these sensors is dependent on the installation, and its value needs to be estimated. Second, the bending of the boom is modeled so that two calibration parameters need to be adjusted (see Section 3.5). Third, the pose of the laser scanner, which is used to observe the targets in the calibration, needs to be estimated.

The selected parameters (three offset values for the position sensors, two spring's torsion coefficients for the boom bending model, and three pose parameters for the laser scanner) were calibrated using a calibration data set (Test A) collected in an obstacle-free environment using all crane joints and driving the crane to multiple different postures (see Figure 10 for the boom-tip trajectory).

Using the 511-s long Test A data set, Method SD measured target positions and the reference crane posture (see Sections 3.3 and 3.5) were collected. Only measurements from time steps, where Method SD succeeded (i.e., candidates were both found and associated correctly) and where the detection range of the both targets was between 1.8 and 8 meters, were accepted for the calibration (67.5% of the measurements in the calibration data set). With these constraints, Method SD is unbiased (zero mean), range errors are within $\pm 3$ cm, and angular errors are within $\pm 0.3^\circ$ as found in a separate test performed to validate the candidate positioning part of Method SD (see Figure 8).

The estimation of parameters is conducted by minimizing an Euclidean distance in the $p$–$z$ plane between two entities, namely, the reference target positions obtained from hydraulic cylinder length measurements and the laser measured target positions obtained using Method SD. Specifically, we obtain the reference target positions by plugging the joint angles of Equation 1 with gravity corrections from Equation 27 into Equation 3, and measured target positions are
TABLE 6  Estimated calibration parameters for the system setup

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value (m)</th>
<th>Explanation</th>
<th>Used in</th>
</tr>
</thead>
<tbody>
<tr>
<td>d_{1, bias}</td>
<td>0.879</td>
<td>Zero offset for the lift cylinder length</td>
<td>(1)</td>
</tr>
<tr>
<td>d_{2, bias}</td>
<td>1.137</td>
<td>Zero offset for the transfer cylinder length</td>
<td>(1)</td>
</tr>
<tr>
<td>d_{3, bias}</td>
<td>1.948</td>
<td>Zero offset for the extension length</td>
<td>(1)</td>
</tr>
<tr>
<td>ρ₀</td>
<td>−0.034</td>
<td>Coordinate of the laser scanner in the p-z plane</td>
<td>5</td>
</tr>
<tr>
<td>z₀</td>
<td>1.482</td>
<td>Coordinate of the laser scanner in the p-z plane</td>
<td>5</td>
</tr>
<tr>
<td>ϕ₀</td>
<td>2.69°</td>
<td>Rotation offset of the scanner</td>
<td>5</td>
</tr>
<tr>
<td>k_2</td>
<td>1.1 × 10^6 Nm/rad</td>
<td>Spring’s torsion coefficient for the lift joint</td>
<td>(27)</td>
</tr>
<tr>
<td>k_3</td>
<td>6.5 × 10^5 Nm/rad</td>
<td>Spring’s torsion coefficient for the transfer joint</td>
<td>(27)</td>
</tr>
</tbody>
</table>

obtained by plugging Equation 6 into Equation 5. Formally, the parameter estimation is done with an error function

\[
E = \sum_{k=1}^{N} w(k) \left( C_w \| \mathbf{p}_{t,11} - \mathbf{p}_{t,1} \|^2 + \| \mathbf{p}_{t,12} - \mathbf{p}_{t,2} \|^2 \right),
\]

(28)

where \( \mathbf{p}_{t,11} \) and \( \mathbf{p}_{t,12} \) are the \( p-z \) plane positions of the detected targets 1 and 2 (with Method SD) and \( \mathbf{p}_{t,1} \) and \( \mathbf{p}_{t,2} \) are the same target positions using the reference model. The total error \( E \) of Equation 28 is a sum from the first to the last \( N \) measurement in the time series with a time step \( k \). For each time step, we define a weight \( w(k) \), where a value 0 is set for all discarded measurements (i.e., measurements not in the accepted range or Method SD failed). A weight constant \( C_w = 4 \) is used in the minimization. This gives the first target more weight, because the positioning of the second target is dependent on the position of the first target. In detail, the first target is dependent on five parameters \( (d_{2, bias}, k_2, ρ₀, z₀, \phi₀) \) and the second one on all eight listed in Table 6 \( (d_{3, bias}, d_{4, bias}, k_3, \) and the previous five).

In the accepted share of the calibration data, Target 2 is more often at middle ranges, but the gravitational effects are maximal when the extension boom is at its maximal reach, that is, when the range of Target 2 is the largest. Thus the weight \( w(k) \) in Equation 28 is set to an inverse of the estimated density of the detected ranges of Target 2. These densities are estimated by calculating a normalized histogram of range measures of Target 2 positions. This inverse weighting by the range distribution of Target 2 in the calibration data is needed to give more equal weights for different crane postures in the minimization.

The computational minimization of Equation 28 was done using Matlab’s numerical minimization function \texttt{fminsearch}, which uses the Nelder-Mead simplex algorithm (Lagarias, Reeds, Wright, & Wright, 1998). The obtained calibration parameters are presented in Table 6.

Later in the Results section it is shown that Method SD outputs zero mean errors with a small variance for Test A (the calibration data set, see also Figure 11). Similarly, in the other tests all those measurements which were correctly detected and associated in Method SD have zero mean errors. In addition, Test A covers a large share of the possible postures (as shown later in Figure 10). Therefore, we can deduce that the calibration has succeeded accordingly.

4.3 Calibration of control signal models for the crane joint velocities

The calibration parameters \( K_c, D_c, \) and the time delay \( Δk \) of Equation 17 in Section 3.4.1 are estimated using a separate identification data set, in which control signals of hydraulic valves are compared to reference cylinder velocities. The calibration is done separately for each cylinder \( c = \{2, 3, 4\} \). Note that we do not need a model for the first cylinder as the slew angle is measured directly.

Time delay \( Δk \) for each cylinder \( c \) is estimated using a correlation between control signals and reference cylinder velocities with different time offsets. These control signals were sampled at 75 Hz frequency similar to laser scanner and reference measurements. Maximally correlating values of time differences \( Δk \) were selected and the found values are shown in Table 7. After obtaining the time delay for each cylinder, the parameters for nonlinear control model (defined in Section 3.4.1) were estimated by iteratively minimizing an error function

\[
E_c = \sum_{k=1}^{N} w_c(k) (\dot{d}_c(k) - \dot{d}_{ref}(k))^2,
\]

(29)

where \( \dot{d}_c(k) \) is the modeled velocity in Equation 17 and \( \dot{d}_{ref}(k) \) is the reference velocity of cylinder \( c \) at a time step \( k \). We obtained the reference cylinder velocities by recording the cylinder position measurements from our crane as they were easily available. Alternatively, we could have used the laser scanner to produce the reference for this calibration by computing the crane posture using Method SD and then used the inverse model in Equation 18 to compute cylinder positions from it. In either way, adjacent cylinder position measurements are differentiated and low-pass filtered to obtain the reference velocities.

The weight \( w_c(k) \) is required to set weight of discarded measurements to zero as accepted measurements are given a value one. Some measurements were manually discarded from the data set as they had totally uncorrelated control and velocity values, see the red crosses in Figure 9. These may be caused, for example, when multiple hydraulic valves are simultaneously fully open and the capacity of the hydraulic pump is not sufficient to provide adequate liquid flow to all of the used cylinders.

Equation 29 is minimized for each cylinder \( c \) separately using Matlab’s numerical minimization function \texttt{fminsearch}, which uses the Nelder-Mead simplex algorithm (Lagarias et al., 1998). The obtained

TABLE 7  Estimated calibration parameters for the hydraulic cylinder control input model

<table>
<thead>
<tr>
<th>( c )</th>
<th>( K_c^- (m/s) )</th>
<th>( K_c^+ (m/s) )</th>
<th>( D_c^- )</th>
<th>( D_c^+ )</th>
<th>( Δk )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.00216</td>
<td>0.00077</td>
<td>−19.8</td>
<td>17.5</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>0.00175</td>
<td>0.00110</td>
<td>−20.1</td>
<td>12.6</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>−0.00435</td>
<td>−0.00477</td>
<td>−25.6</td>
<td>20.4</td>
<td>7</td>
</tr>
</tbody>
</table>
calibration parameters for the hydraulic cylinders are listed in Table 7, and used data points and the fitted models are shown in Figure 9.

4.4 | Outline of the Tests A–E for the proposed CPPF

The proposed CPPF is tested in five different tasks in the Results section. The properties of these tests are outlined here. The first, Test A, is the easiest one, since the crane was moved in a free space without any foliage or obstacles, the machine being in a flat-asphalt environment. Test A data set is used for estimating the calibration parameters of the system setup with Method SD: Simple target detector (defined in Section 3.3). The data set is 511 s long and it contains 9574 laser scans at the frequency of 18.75 Hz.

The second test, Test B, is measured under a broad-leaved tree (a silver birch) that induces significant foliage, introducing multiple obstructions to the data. Test B is 155 s long and it contains 2,902 laser scans. The third test, Test C, also has a lot of occlusions, since the crane is handled in the vicinity of a spruce tree with close to maximum elongation. Test C contains 4,944 laser scans taken during a time interval of 264 s.

The main difference between the Tests B and C is that in C the crane is mostly operated at its maximum reach, while in Test B, the tip position is handled at shorter ranges for most of the time. The occluding tree is nearer in Test B, which introduces more obstructions closer to Target 1. The Tests A, B, and C have simulated control signals based on real uncertainties of the hydraulic control model found in Section 4.3 as the second target might be confused with the tool. Also, this data set, which is also used in Test E, is the only one where hydraulic signals were recorded from the vehicle bus and they are used in the estimation instead of simulated control signals employed in the three first tests.

Finally, Test E is a tolerance test, where our claim of weatherproofness is tested. We assume that bad weather conditions such as snow, rain, and minor equally spread dust or thin fog can be represented as random obstructions to the line of sight which results into respective random shortening of range measurements. To test the tolerance, we draw random simulated obstructions to the laser scanner readings for the data set of Test D between 400 and 600 s (containing 3,748 laser scans). This short time range was selected to save computation time. Nonetheless, this range includes a large enough variability in all estimated crane joint variables. Algorithms were run multiple times with increasing amounts of simulated obstructions. Technically, obstructions are introduced to the scanner data by randomly adding simulated measurements between the scanner and the laser range observation with a function:

\[
\hat{r} = \min \left( r, \frac{\log (1 - U)}{\log (1 - \xi)} \right),
\]

where \( \hat{r} \) is the modified range measurement, \( U \sim U(0, 1) \) is a sample from standard uniform distribution (between 0 and 1), and \( \xi \) is the probability of an obstruction per meter. The equation is an inverse function for exponential attenuation as a function of range. The minimum is selected between the original measurement (\( r \)) and a randomly drawn, simulated obstruction.

5 | RESULTS

The aim of the presented results is to evaluate our hypothesis that introducing control signals of the hydraulic valves to the crane posture estimate increases its reliability, especially when the line of sight to the scan targets is obstructed. This is why we compare the
FIGURE 10 The trajectory of the boom-tip position in the \( \rho-z \) plane during each of the tests. The white area shows all possible boom-tip positions that are reachable by the crane, although here the ground resided at \(-1\) m.

FIGURE 11 Error statistics for Test A (a calibration data set) are visualized with a box-and-whiskers plot and also the underlying histogram is visualized under the box-and-whiskers plot. Detected outliers (quality <0.5) are marked with red + signs.
Error statistics for Test B (foliage under a tree) are visualized with a box-and-whiskers plot and also the underlying histogram is visualized under the box-and-whiskers plot. When a whisker does not fit into the shown range, its end position is marked under the corresponding whisker. Detected outliers (quality < 0.5) are marked with red + signs.

Error statistics for Test C (a long distance test) are visualized with a box-and-whiskers plot and also the underlying histogram is visualized under the box-and-whiskers plot. When a whisker does not fit into the shown range, its end position is marked under the corresponding whisker. Detected outliers (quality < 0.5) are marked with red + signs.

Table 8: RMSE of the Tests A, B, C, and D

<table>
<thead>
<tr>
<th>Test</th>
<th>Method</th>
<th>$\theta_2$ error (deg)</th>
<th>$\theta_3$ error (deg)</th>
<th>$d_x$ error (m)</th>
<th>Tip position error (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>SD</td>
<td>0.066</td>
<td>0.241</td>
<td>0.011</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>CPPF</td>
<td>0.137</td>
<td>0.403</td>
<td>0.012</td>
<td>0.019</td>
</tr>
<tr>
<td>B</td>
<td>SD</td>
<td>0.213</td>
<td>8.292</td>
<td>0.272</td>
<td>0.463</td>
</tr>
<tr>
<td></td>
<td>CPPF</td>
<td>0.072</td>
<td>0.230</td>
<td>0.016</td>
<td>0.019</td>
</tr>
<tr>
<td>C</td>
<td>SD</td>
<td>0.054</td>
<td>2.081</td>
<td>0.339</td>
<td>0.380</td>
</tr>
<tr>
<td></td>
<td>CPPF</td>
<td>0.100</td>
<td>0.320</td>
<td>0.040</td>
<td>0.043</td>
</tr>
<tr>
<td>D</td>
<td>SD</td>
<td>0.078</td>
<td>0.910</td>
<td>0.020</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>CPPF</td>
<td>0.122</td>
<td>0.306</td>
<td>0.009</td>
<td>0.014</td>
</tr>
</tbody>
</table>

fails. However, the CPPF method manages to estimate the posture from the control signals. The increased uncertainty is expressed visibly in the behavior of the quality self-measure (see the bottom plot of Figure 14). The CPPF method performance in overall statistics is also good and is shown in Figure 13.

In the longest test, Test D (statistics shown in Figure 15), both methods work quite well. Method SD does a few false detections, and, therefore, it has large maximal errors in Figure 15. However, it can be seen in the time series plot in Figure 16 that these events are rare. This test contains only a few occlusions of Target 2 and thus also Method SD
works quite well. This test also shows that both methods can be used with a freely swaying tool. In addition, as Test D data set is the only one which contains real hydraulic signals, it is important to note that there are no significant differences in the statistics between Tests A, B, C, and D for the proposed CPPF.

Finally, simulated weatherproofness of the proposed methods was tested in a tolerance test (Test E). Randomly drawn obstructions were introduced to shorten the laser scanner range measurements within a subset of Test D data. As can be seen from Figure 17, the proposed CPPF can withstand this noise well until there is more than 10% probability of an obstruction per each meter of medium where the laser pulse travels. This means that the proposed CPPF only fails after the targets are hardly visible through noise. As a comparison, the SD method starts to fail already when only a slight amount of obstructions are introduced to the measurements. Similarly, its measurement errors increase as the probability of obstructions is increased.

6 | DISCUSSION

In this work, we have made an effort to cover all the relevant aspects for using the proposed CPPF to estimate the posture of a hydraulic crane so that the method would be reproducible—both for academic and industry purposes. In this work, we have presented a method to reliably estimate the posture of a hydraulic forestry crane. The setup was tested in many different tests containing a significant amount of foliage, a freely swaying tool, and simulated random obstructions in the
measurements. All our methods—including the reference—were operated in faster than real-time with a normal laptop computer using Matlab software, to show that the proposed methods can be later implemented as a real-time measurement system.

Both the proposed CPPF method (defined in Section 3.4) and simple target detector (defined in Section 3.3) behave similarly in the first test (Test A) without any foliage (see statistics in Figure 11 and RMSE in Table 8). However, in the other tests, the proposed CPPF has significantly better results as it is able to reliably track both of the targets almost all the time. The simple target detector could maybe be improved by adding heuristics to avoid tracking wrong candidates. However, it would still give significant amount of failed measurements without providing any idea where the crane is. Thus we have proven our hypothesis that the use of control signals allows for a significantly more robust crane posture estimate. Especially Tests B and C show that when a target is occluded, the simple target detector fails, but the proposed CPPF is still able to give an accurate estimate. The tests also show (especially Test B with most occluding foliage and Test E with random obstructions) that the proposed CPPF is robust against random measurement errors between the scanner and targets. These kinds of errors may be caused by obstacles or bad weather conditions (e.g., rain, snow, dust, or fog) making the medium less transparent. As the used scanner is rated for outdoor use, it withstands freezing temperatures, rain, snow, and it has automatic fog correction, which increases laser power if echoes are missed (SICK AG, 2006); the sensor is a good choice for this task.

We have shown that a minimal instrumentation containing only the laser scanner, two attached scan targets and a rotation instrumentation of the slew joint (which rotates the pillar where the scanner is mounted) is enough to produce both an accurate crane posture estimate and to simultaneously collect a 3D point cloud (see Figure 18 for an example point cloud). In the future, the same instrumentation could...
be used to measure and model the environment, for example, nearby trees and ground in the forest. This is useful for estimating, for example, the forest inventory, stem curves and volumes of tree trunks before cutting, or tree maps and paths for an autonomous forest machine. The electronic parts of our minimal instrumentation reside in the rear end of the crane (near cabin), which significantly reduces the need for cabling. Also the rear end of the crane rarely hits any obstacles like trees or ground, and thus the sensors are unlikely damaged if the proposed setup is used in normal operation. Both scan targets are magnetically attached onto the crane, and they simply fall of instead of being damaged if they collide with obstacles.

The nearest comparable setup found in the state-of-the-art section is the IMU instrumentation of a similar type of a hydraulic crane by Vihonen et al. (2014, 2016). Their best results had RMSE of 0 is the IMU instrumentation of a similar type of a hydraulic crane by damaged if they collide with obstacles.

An accumulated point cloud around 125 s from Test C when the boom tip is driven into a spruce tree. The crane is drawn as a gray line, laser scanner is located at the green cross, and targets are the two blue dots. Range measurements associated with Targets 1 and 2 are removed from the point cloud, and the cloud is colorized in hue, saturation, lightness (HSL) color space such that hue indicates the height of a point, lightness the range of a point from scanner, and saturation is a constant one. The 3D visualization is made with Point Cloud Library (Rusu & Cousins, 2011)

The proposed CPPF method estimates the posture of the crane accurately without the need for a bending model. In contrast, the current industrial solutions (e.g., Cranab, 2015; Suuriniemi, 2013) and our reference model (introduced in Section 3.5) using the measured lengths of the hydraulic cylinders (defined in Section 3.5) requires information about masses and angular string constants to model the bending caused by gravity. Without the proposed bending model, our reference would not be sufficiently accurate to be used as a comparison for the proposed laser-scanner-based methods. The crane boom bends more than 10 cm with the maximum elongation without any load, and significantly more under load. By directly measuring the tip position with a laser scanner, the end-effector displacement error caused by the bending of the boom can directly be measured instead of requiring a calibrated multiparameter model to obtain it. Note that the limitations of our reference model restricted this study to conditions where the reference can be trusted. In other words, we had to use known weights instead of unknown weights and to avoid vibrations instead of covering all the range of normal crane working speeds. In the future, the proposed system might be extended to estimate the unknown weights of the lifted trees. This would require designing the minimum instrumentation so that all additional parameters can be estimated.

There are a few limitations in the proposed methods. First, there is inherent uncertainty in the control signals, and it is further increased by the noise added in the prediction phase of the CPPF method. This leads to slightly larger statistical errors when compared against Method SD in laboratory conditions, that is when both of the targets are clearly visible and there are no obstructions in the field of view of the scanner. However, in practice, if obstructions are to be expected, Method CPPF is always more reliable than Method SD. Second, our proposed methods have a lower update frequency than a joint position instrumentation with encoders which can measure at frequencies of hundreds of hertz. The used laser scanner (SICK AG, 2006) has a frequency of 75 Hz and four adjacent measurements are combined to get a higher angular resolution of 0.25°. Thus our laser-scanner-based methods provide crane posture estimates at only about 19 Hz. A faster scanner could give a slightly higher frequency, but still these methods would give significantly less measurements per second than encoders. This would be a limitation at least if high-frequency phenomena are looked for. However, in many cases the crane is slow to react and even a 10-Hz update frequency is sufficient for control purposes (e.g., Kalmari et al., 2014). The third limitation is that the pose of the platform and bending of the first section of the crane (the pillar) is not measured in the proposed method. If these are required, the changes in orientation of the laser scanner should be measured with, for example, a 3D inclinometer.

There are ways to overcome these limitations. Accuracy of the crane posture estimate would be increased if the crane motion could be predicted more accurately from the control signals. These prediction signals are also vulnerable to changes in calibration parameters if, for
example, the temperature or viscosity of the hydraulic fluid changes. Also, the proposed CPPF could be modified to include some of the calibration parameters as states to estimate them online, for example, gains of control signals of the hydraulic actuators could be changed slowly online to adapt to changing temperatures and fluid viscosities. However, this would increase the computational complexity. The techniques of CPPF could also be combined with other sensors, for example, those used for inertial measurements (e.g., Vihonen et al., 2014, 2016). This would increase the accuracy of the crane posture estimate, since the inertial sensors could provide significantly more accurate estimates of the actual movement of the crane than the currently used control signals for the hydraulic valves. In addition, inertial sensors could give reasonably higher measurement frequency, and also the dynamic behavior of the crane could be better tackled. However, the inertial sensors would increase the complexity and introduce more sensors, cabling, software, and calibration parameters into the system setup.

The optical instrumentation for posture estimation presented here might be extended so that on-line weight estimation for unknown lifted items could be possible. This could also be attained by estimating crane bending through laser scanning. The minimal setup would then need to be planned accordingly to account for the increased amount of parameters to be solved.

7 | CONCLUSION

In this work, we proposed a forest- and weatherproof minimal instrumentation solution for the crane posture estimation for flexible hydraulic cranes. In summary, we defined two real-time-capable methods to estimate the posture of a hydraulic crane using a mounted 2D laser scanner and two scan targets, which are short magnetically attached metal tubes always in the field of view of the scanner. The first method (defined in Section 3.3) takes single scans as input and searches for circular 6 cm wide objects in the scan. The second method (CPPF, defined in Section 3.4) is a particle filter implemented to probabilistically combine laser scanner measurements with control signals of the hydraulic crane. We also showed how to calibrate the measurement setup and tested our methods thoroughly by comparing them with a reference posture (defined in Section 3.5). It is made up from the length measurements of hydraulic cylinders using a kinematic model of the crane, while correcting for its bending under gravity.

In our field tests, we have shown that obtaining the crane posture estimate from both laser scanner measurements and control signals using the proposed CPPF method is more reliable than using only laser observations. In particular, the crane posture estimation can be done without large errors even when the targets are occluded behind foliage or when the control signals contain erroneous information about the crane movement. We have shown that the proposed CPPF method is tolerant to high amount of obstructions in the laser scanner data, which could be caused by atmospheric conditions or obstacles in the line of sight. In the future, knowledge may be gained through comprehensive tests in rain, snow, and dust, and tests with different cranes and laser scanners. The method should also be tested as a part of a real-time control loop.

The proposed method advocates for a new paradigm in automating flexible cranes in the forest industry. Our work enables a robust and accurate online solution for forest machine manufacturers to measure the posture of a flexible forestry crane. The proposed method is quite universally applicable for hydraulic cranes with a telescopic extension boom. The proposed method allows for other benefits as well. As only a minority of the laser range observations is used to measure the crane posture, the rest are useful for measuring the surrounding environment. It would be a radical change, if forest machines could collect forest inventory information, and map and measure trees before felling them. This will likely enable a new generation of industry-fabricated machines.

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ORCID

Helikki Hyyti http://orcid.org/0000-0003-4664-6221
Ville V. Lehtola http://orcid.org/0000-0001-8856-5919
Arto Visala http://orcid.org/0000-0001-6253-8357

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