Original scientific paper

Estimating the Position of the Harvester Head – a Key Step towards the Precision Forestry of the Future?

Ola Lindroos, Ola Ringdahl, Pedro La Hera, Peter Hohnloser, Thomas Hellström

Abstract

Modern harvesters are technologically sophisticated, with many useful features such as the ability to automatically measure stem diameters and lengths. This information is processed in real time to support value optimization when cutting stems into logs. It can also be transferred from the harvesters to centralized systems and used for wood supply management. Such information management systems have been available since the 1990s in Sweden and Finland, and are constantly being upgraded. However, data on the position of the harvester head relative to the machine are generally not recorded during harvesting. The routine acquisition and analysis of such data could offer several opportunities to improve forestry operations and related processes in the future. Here, we analyze the possible benefits of having this information, as well as the steps required to collect and process it. The benefits and drawbacks of different sensing technologies are discussed in terms of potential applications, accuracy and cost. We also present the results of preliminary testing using two of the proposed methods.

Our analysis indicates that an improved scope for mapping and controlling machine movement is the main benefit that is directly related to the conduct of forestry operations. In addition, there are important indirect benefits relating to ecological mapping. Our analysis suggests that both of these benefits can be realized by measuring the angles of crane joints or the locations of crane segments and using the resulting information to compute the head's position. In keeping with our findings, two companies have recently introduced sensor equipped crane solutions.

Keywords: boom tip control, automation, ALS, sensors, harvester data

1. Introduction

Forest machines used for fully mechanized cut-to-length (CTL) harvesting are technically advanced with the ability to perform complex operations such as automatic mechanical measurement of stem diameters and lengths during harvesting. These measurements are processed in real time to support value optimization when cutting stems into logs. They can also be transferred from the machines and used in central systems for wood supply management by the forest industry (e.g. Eriksson and Lindroos 2014). Information management systems of this kind have been used in Sweden and Finland since the 1990s, and have been refined over time (Anon. 2010). Whereas spatial data were initially only gathered at the stand level, it is increasingly common for this information to be disaggregated within stands.

The main factor driving this increase in resolution is the now common use of the global navigation satellite system (GNSS) to determine machine positions. This positional information is used to link data for harvested trees to the machine's position when the tree was harvested (e.g. Bollandsås et al. 2011). However, the positional accuracy of current systems is limited by two key problems. First, GNSS data typically have a relatively low positional accuracy of ±10 meters in forest environments (Andersen 2009, Rodrigues-Pérez et al. 2007, Naesset and Jonmeister 2002). Second, the actual position of the harvester head relative to the machine's position is generally not known beyond the fact that it must be somewhere within the crane's reach, which is typically around 10 m. This introduces an accuracy error comparable in magnitude to that inherent to the GNSS data. Despite these limitations, current positioning systems have found some practical applications (e.g. Möller et al. 2012).

The potential of using measurements of the spatial position of the harvester head as a low cost method for forest mapping was outlined long ago (Stendahl and Dahlin 2002). It might well be that increased accuracy will unlock many intriguing possibilities for future forestry and related areas. However, there has been little progress towards this objective, and the full potential of existing data gathering methods has not yet been embraced due to the low accuracy of the positional data. While methods for gathering more accurate positional data could certainly be developed, it has not yet been demonstrated that the benefits of doing so would justify the costs. Ideally, the potential benefits of such undertakings should be analyzed before allocating scarce development resources (cf. Lindroos 2012, Berg et al. 2014).

Today's technology makes it possible to gather data at various levels of accuracy and cost. Since different applications are likely to have different accuracy requirements, it is important to match the level of accuracy to the desired objectives. In this article, we investigate the possible benefits of gathering highly accurate spatial data on the position of the harvester head, and compare these benefits to the effort required to gather and process such data. This information is useful for understanding the benefits and drawbacks of different sensing technologies in terms of their applications, accuracy and costs.

To this end, we start by analyzing the possible benefits of knowing the harvester head's position, and the possible methods of acquiring such information. We then compare the features and limitations of these methods to the accuracy required to achieve each benefit. This leads to an evaluation of the benefits and methods by which they could be realized. To support our findings, we summarize results from feasibility tests on two of the proposed methods and then conclude with a discussion section.

2. The benefits of knowing the position of the harvester head

Knowing the location of the harvester head confers a number of benefits that can be divided into two categories. Indirect benefits are those that relate to mapping of the forest environment. These benefits are realized by using the position of the harvester head to estimate the positions of other objects. Direct benefits relate to mapping and controlling the movement of the machine; in such cases, information on the position of the harvester head is used to guide the harvesting work. Here we list and discuss benefits of both kinds. While the list is quite extensive, the potential benefits are numerous and so we suspect that readers may be able to identify some that we have overlooked.

2.1 Defining accuracy

For each benefit, we provide an estimate of its accuracy requirements. Naturally, excessively accurate positional information is not a problem, whereas insufficient accuracy may make certain benefits impossible to achieve. Thus, most applications benefit from having the highest possible accuracy. However, increased accuracy normally implies increased costs, so for each benefit we aim to identify the minimum level of accuracy needed to achieve the relevant functionality. For example, in some applications, it is crucial to know which stand a tree originates from. Accuracy at the mm level would provide such information, but would be excessive; the objective could be achieved equally well with an accuracy of 10 to 20 meters. Therefore, we have tried to estimate a reasonable minimum level of accuracy for each application, while noting that the actual accuracy required in a given situation may be somewhat variable, depending on local conditions. Our aim is to broadly capture and contrast the levels of accuracy required to achieve different benefits, rather than to exactly specify the accuracy required to achieve a particular goal. Therefore, we have chosen to focus on positional accuracy in the horizontal plane, and accuracy requirements are defined in terms of a set of concentric circles centred on the true position of the harvester head. The radius of the largest circle containing the estimated position of the head is used to specify the level of accuracy required. Five accuracy categories are considered: >10m, m, dm, cm and mm. If a benefit requires mm accuracy, the estimated position of the head must be within several millimetres (with an upper limit of 1 cm) of its true position. The cm, dm, and m categories indicate that the estimated position must be within several centimetres, decimetres or meters of the true position, respectively. An accuracy requirement of >10 m indicates that the benefit in question can be achieved if the estimated position is within a circle having a radius of >10 m. We did not define an upper limit for this category because it is used to characterize benefits whose accuracy requirements are relatively low, but naturally there is always some limit.

2.2 Mapping the forest environment

Information about the forest environment is required to support various forestry operations and the study or management of forest ecology. Such information is useful for answering questions relating to the nature of the standing forest (e.g. how much forest with specific properties do we have?) and operational questions (where should the machine drive, where have trees been harvested?). Here we focus on the benefits of knowing where trees are (or have been) spatially positioned and the location of the harvester head.

2.2.1 Reconstructing representative 3D models of forests

The most obvious application for data on the location of the harvester head is that it could be used to update existing information on the positions of trees during harvesting. Analysis of such data would make it possible to virtually reconstruct the harvested trees based on the properties of their logs and thereby generate a 3D model of the harvested forest. In current systems, all trees harvested when the machine is in a given location are assumed to be located in the same place as the machine, which makes it appear as though all of the harvested trees were growing on top of each other (Anon. 2010). This is a well-known limitation, and tree-specific positional data could easily be incorporated into existing data gathering protocols if there were some method of gathering it. In this way, it would be possible to use data gathered during conventional harvesting to study the spatial distribution of tree species and sizes in the clearcut forest. Information obtained by such large scale destructive sampling would probably be useful in silvicultural applications and forest ecology. For instance, it would provide large amounts of representative data that could be used in spatial forest modelling (e.g. Arii et al. 2008, Thorpe et al. 2010, Fortin et al. 2013). Perhaps more interestingly, 3D forest models of this sort could be used to predict the features of unharvested forests by analyzing the harvester data in conjunction with information gathered by remote sensing (see below).

»Estimated accuracy need«: m to dm. The most important information in such datasets is the positions of trees relative to one another. Accuracy errors of several meters could thus potentially be tolerated if they were systematic.

2.2.2 Training of ALS and other remote sensing methods

Recent studies have demonstrated that combining automatically generated 3D forest maps with airborne laser scanning (ALS) could be extremely useful. ALS can provide very accurate geographical information for large areas of land. Height models of tree crowns and the ground can be generated from ALS data and processed using tree crown segmentation algorithms to produce global tree maps with complete coverage. Several variables related to crown shape and size, such as the stem volume (Hyyppa et al. 2008), can then be estimated.

Today, manual field inventories conducted in geo referenced sample plots are still needed to establish the models used to predict stem attributes from ALS data (Naesset et al. 2004). In the future, local tree maps generated by harvesters during normal forestry operations could make it possible to collect more reference data to improve predictions and obtain more detailed stem data. In this way, normal harvesting would serve as a form of destructive sampling, yielding data that could be used to make inferences about similar forest areas. Gathering data in this way during continuous large scale forest operations would enable the creation of a system for the training and refinement of ALS based algorithms for large scale studies. Tree data collected by harvesters during harvesting operations have previously been used to train ALS data, but it has either been done based on the machine position, in which case the problem of having multiple trees with the same estimated position arises (Bollandsås et al. 2011), or based on manual positioning information that was linked to the tree data after harvesting (Holmgren et al. 2012, Barth and Holmgren 2013).

Local maps generated on the basis of information on the position of the harvester head relative to the machine must be combined with global ALS maps in order to enable the development of improved ALS models. In other words, the trees in the local maps generated from the harvester data must be matched to trees in the ALS map. Matching presents various challenges. First, a tree's top and stump may have different locations if the tree leans. Second, there may be limitations on the ability to identify individual trees within the ALS data. Third, matching may be challenging due to poor accuracy in machine positioning, although this problem could be alleviated by using matching algorithms that only take positional information from a GNSS as starting positions (Rossmann et al. 2009, Rossmann et al. 2010). Such an approach could be used as an alternative or complement to GNSS, to help improve its relatively poor positional accuracy in forest environments (Andersen et al. 2009, Rodríguez-Pérez et al. 2007, Naesset and Jonmeister 2002). ALS models could thus be refined on the basis of harvester head data and used to feed information back into GNSS systems in order to increase their positional accuracy.

Naturally, this is not the only way of improving the quality of the data on the machine's position. Several proposed solutions involve sensors mounted on forest machines to create local tree maps of their environments in real time (Hellström et al. 2009, Hellström and Ringdahl 2009, Öhman et al. 2008). This is typically achieved with a 2D laser scanner combined with SLAM (simultaneous localization and mapping) algorithms (Wang et al. 2005, Miettinen et al. 2007, Huang et al. 2008). To achieve high accuracy in the SLAM algorithms, the centre of the tree must be accurately determined (Dissanayake et al. 2001), which is quite challenging due to the irregular shapes of tree trunks and their variability over time (see e.g. Ringdahl et al. 2013).

»Estimated accuracy need«: dm to m. The most important aspect of spatial data for individual trees is the accuracy of the relative position of trees. In this application, the positions of the harvested tree (as judged by the data from the harvester) are matched to the estimated location of trees from the ALS data. Consequently, as long as there is a good match between the two datasets, they can be used to support one another, reducing the need for high accuracy in the head position data. However, if the two datasets are poorly matched, for example if some harvested trees cannot be discerned in the ALS data, highly accurate harvested tree positions would be very important because they would be used as a basis for correcting the ALS algorithms. Overall, however, accuracy errors of several meters could probably be tolerated if they were systematic.

2.2.3 Timber traceability

Forest owners must be able to demonstrate that their production and harvesting operations are conducted responsibly when supplying demanding end users. It is, therefore, important to ensure that all product components are traceable. For tree based products, this means having the ability to unambiguously determine where the trees used in a given product were growing before being harvested. Traceability requirements can be met with very low levels of accuracy, and the levels achieved by current machine positional data are generally sufficient. In fact, greater accuracy would be of little use and there are many harder challenges that should be addressed first to increase traceability. The key missing link is the ability to link the data gathered for individual logs at different stages in the chain of custody, and to then trace the fate of the log parts as they are mixed and blended (this mixing and blending may be extensive – sheets of paper are made of dissolved fibres from thousands of trees). Several methods for tracing the fate of individual logs have been proposed (e.g. Hakli et al. 2010, Murphy et al. 2012, Seidel et al. 2012, Athanasiadis et al. 2013), but few are implemented on a large scale.

»Estimated accuracy need«: >10 m. There is generally little need to provide anything more than the stand from which a given tree was harvested, and in fact even this low level of accuracy may be excessive. The upper limit on the tolerable accuracy for this application depends on stand size, the demands of the end users, and potentially future legal requirements.

2.2.4 Improved characterization of product properties

It is well known that the properties of a tree's wood depend on the conditions under which it is grown. Silvicultural regimes are thus designed to optimize wood properties such as density, fibre angles, knot occurrence and taper (Yang 2002, Eriksson et al. 2006, Persson 1977). Technological developments have made it possible for harvesters to gather data while bucking trees into logs, including data on wood properties that had not previously been considered such as stiffness (Murphy 2014). Furthermore, while trees of the same species can also vary in their chemical composition (e.g. Arshadi et al. 2013), data on the chemical composition of wood is rarely used during industrial processing. However, the ongoing development of new wood products and processes, such as biorefining, mean that it may become increasingly important to identify trees with desirable chemical properties. Data collected by harvesters can already provide industry relevant information at the stand level (Nordström et al. 2010). However, some important properties are likely to be related to the tree's geo-spatial properties. It may, therefore, be important to determine the locations of individual trees on a global map that also records data on local spatial conditions such as stand density. Information of this sort, such as the slope of the land a tree is growing on, the nature of the soil at the site, or the density of the tree stand can also be captured manually by the operator. However, the need for manual recording could be reduced or eliminated if better positional data were available. As with traceability, this would require the ability to link data for individual logs from multiple points in the supply chain. However, sorting on the basis of product features could be done at a relatively late stage in the supply chain, thereby avoiding the need for costly sorting in the forest.

»Estimated accuracy need«: >10 m to 1 m. There is generally little need for greater positional accuracy than that provided by existing systems which simply record the machine's position. However, the ability to provide more detailed information on the properties of raw materials could potentially enable the development of fine-tuned industrial processes that require feedstock with tightly defined properties. It is, therefore, possible that the ability to deliver would create a requirement for greater accuracy.

2.2.5 Calculating the density of tree removal

Thinnings are normally performed at an intensity that is chosen so as to leave a residual stand with the density required to provide the best possible conditions for future development. Traditionally, thinning intensities are defined using mean values for entire stands, often in terms of the total basal area that should be harvested. A given intensity can be achieved by felling several thin trees or fewer thicker trees. It can, therefore, be difficult for operators to decide which trees to fell to achieve the desired intensity. Moreover, the tree density normally varies somewhat within a stand, making it even more difficult to decide which trees to fell. In some countries, this problem is addressed by marking trees to be harvested. However, in Nordic countries, operators select which trees to harvest. While their selections are normally considered to be quite reasonable, the selection process requires recurring manual (and thus costly) calibration by the operators. Improvements would, therefore, be beneficial.

Various methods have, therefore, been developed to calculate the density of trees removed per area (Stendahl and Dahlin 2002, Möller et al. 2012). However, these techniques are based on the machine's position, with estimations of the area harvested for given numbers of trees. They are useful since they provide the operator with real time feedback on the harvested density during thinnings, which can be compared to the desired intensity. The ability to determine the harvester head's position would increase the accuracy of these calculations, enabling better thinning and documentation of the variation in removal intensity within a stand. This would be useful in supporting operators' decision making. However, this approach would be a lot more powerful if it were complemented by methods for sensing or deducing the density of the residual stand. Machine mounted sensors could potentially provide information on the residual stand (e.g. Rossman et al. 2009), but it will be challenging to develop appropriate and affordable sensor technologies. Alternatively, and perhaps more practically in the near term, information on the intensity of removal could be integrated with ALS data on the properties of the original stand. Provided that ALS data can be used to reliably identify small trees in the lower parts of the canopy, spatially specific thinning regimes could be designed and implemented by calculating the density of the residual stand as the difference between that of the original stand (determined from the ALS data) and the harvested density (determined from the data supplied by the harvester). Harvester head positioning data could thus enable operators to implement desired thinning regimes more easily and accurately.

»Estimated accuracy need«: >10 m to 1 m. Existing methods (Möller et al. 2012) are functional with positional accuracies in the >10 m range, since they use information on the position of the machine rather than the head. A higher positional resolution would be beneficial for the development of detailed thinning regimes, but would probably be most useful for training the ALS models used to estimate the initial stand density and spatially resolve the thinning intensity.

2.2.6 Virtual marking and constraining

If the position of the harvester head was recorded, it could potentially be used as a virtual pen to mark the positions of various features on digital maps of the harvesting site. This would need to be combined with a means for the operator to record the identity of the mapped feature. The most obvious features to record in this way would be the locations of created snags, i.e. trees cut at a greater height than normal. In addition, objects of interest could be mapped by holding the harvester head above or next to them. In this way, the locations of ecologically and/or culturally interesting objects could be reliably recorded on digital maps. Borders of various kinds could be delineated in a similar way, allowing to introduce virtual obstacles to the motion of the harvester and its crane in order to avoid harvest of trees or machine driving in predefined areas.

»Estimated accuracy need«: 1 m in general, but potentially 1 dm if dealing with legal issues such as property boundaries. However, like current digital and paper maps, the generated maps would probably just be used as indicative maps, and field inspections would be required to verify the locations of specific objects. Accuracy at sub meter levels would thus be unnecessary for current applications, although it is possible that accuracy demands would become more stringent as data of this sort became readily available and applications were developed.

2.3 Mapping and controlling machine movements

Reliable and accurate information on the positions of individual machine parts is essential when mapping and controlling machine movements. Consequently, the acquisition and processing of such information is being studied intensively around the world in order to support the development of machines capable of autonomous navigation and performing various other functions (semi) autonomously. In the context of forestry, there has been substantial recent progress in this area (e.g. Hellström et al. 2009, Mettin et al. 2009, Rossman et al. 2009, Rossman et al. 2010, Ringdahl 2011, Ortiz Morales et al. 2014), but industrial acceptance of such approaches has been less widespread than is the case in related fields such as agriculture. Here we discuss the general benefits that could be realized by knowing the position of the boom tip of any forest machine (e.g. harvester or forwarder) because they are not related to ecological data collected during harvesting. In fact, these benefits could in principle be achieved for any machine with a hydraulic crane.

2.3.1 Machine (semi) automation

For most mechanical manipulators, it is important to be able to estimate the position (and orientation) of the end effector in order to implement any form of decision making concerning its actions. This information can be fed into computer algorithms to control the manipulator's movements or to provide information for supervision. The required accuracy of the estimates usually depends on the application. For example, controlling the motion of a manipulator requires high accuracy and fast sampling because the estimates are used by computers as feedback information for motion control. However, if the information is only needed from time to time for supervisory purposes, a wider range of measurement resolutions and sampling speeds may be acceptable.

Ideas of this sort have been studied for some time within the forest machine industry. Recent developments in sensing technologies for cranes have led to the introduction of one of the first commercial products for controlling forestry cranes using computerized algorithms (John Deere 2013). Solutions of this sort are said to provide »boom tip control« (BTC) because the operator uses joysticks to control the tip's movements rather than independently manipulating the movements of individual sections of the crane arm (e.g. Gellerstedt 2002). This has a number of advantages, not least of which is that it reduces the difficulty of controlling the crane, making the process more intuitive and easier to learn while improving the machine's efficiency (Westerberg 2014).

Although the commercialization of BTC represents a milestone for the forest machine industry, various other computer controlled functions have been suggested and developed over the years. For instance the works presented by Shiriaev et al. (2008), Mettin et al. (2009), Westerberg (2014), and Ortiz Morales et al. (2014) discuss future applications in which most crane operations are governed by a mixture of human commands and semi-autonomous functions. A simple example would be a system that allowed a harvester to autonomously approach a tree that has been selected for felling. It would then be possible to use the existing technology to control the gripping and felling of the tree, which could be performed manually or by taking advantage of other modes of interaction such as voice commands. The automation of forwarder cranes would also offer several advantages because it could reduce the operator's mental fatigue by automating the movement of the crane between bunk and log piles. This is also beneficial in terms of efficiency because computers are significantly better than people at identifying optimal working conditions in terms of speed of work, fuel consumption, energy usage, and so on (Westerberg 2014). Additionally, this technology also offers the possibility to improve operator and machine safety by applying virtual restrictions to harmful crane movements.

Despite the various technological advances underpinning these solutions and their commercial success, there are still major challenges to overcome in the automation of forestry machines. A key challenge stems from the highly unstructured nature of the forest environment, which will necessitate the development of reliable sensing technologies. In addition, considerable further progress in robotics will be required to enable fully automated forestry operations.

»Estimated accuracy need«: mm to cm. The required accuracy varies from application to application. However, an accuracy in the centimetre range is essential for efficient autonomous crane movement; lower levels of accuracy would impair the functioning of the control algorithms and risk damaging the machine or trees. The greater the sophistication and autonomy of the control system, the greater the level of accuracy required.

2.3.2 Improving operators' working methods

Operating forest machines is known to be challenging because many tasks must be conducted simultaneously and at high speed (e.g. Gellerstedt 2002, Ovaskainen and Heikkilä 2007). Operators are trained to handle the machines, but as with most trades, there are often several ways of accomplishing a given task, particularly given the heterogeneity of forest environments. It is, therefore, difficult to identify the most efficient working method for a particular situation and task. The development of screen based forest machine simulators has facilitated the training of machine operators, allowing education and evaluation to be conducted in virtual environments (e.g. Ovaskainen 2005). However, the scope for practical evaluation of specific working methods is currently limited. Studies on the time consumption associated with specific elements of a working method can be helpful but their results are not readily translated into assessments of the efficiency of a given approach. A key problem in such analyses is that, while experienced individuals can relatively easily assess the general efficiency of an operator after briefly observing their work, they generally cannot easily explain in detail the reasons for their judgement (Purfürst and Lindroos 2011). However, if crane movements could be monitored, the resulting data might enable the analysis of efficient working methods, which could then be taught to other operators. For instance, Ortiz Morales et al. (2014) have shown that operators' working practices can be improved by monitoring their crane movements and using motion optimization to analyze their working patterns and suggest ways of increasing efficiency. The results of such studies have direct applications in areas such as the training of machine operators, automation, information management and interaction design.

»Estimated accuracy need«: dm. A positional accuracy of a few decimetres should be sufficient to identify the most efficient crane movement patterns for most types of work. Given the great diversity of working conditions encountered in practical forestry and the high levels of variation in the way different operators perform different movements, greater accuracy is unlikely to be particularly useful in this context. Moreover, it is unlikely that an operator would be able to follow a given crane path with better accuracy than some decimetres, given the time constraints that apply during normal work.

3. Methods for estimating harvester head pose

3.1 Working conditions and required features

Before discussing methods that could be used to monitor the position of the harvester head, it is important to define the conditions under which these methods must function. Forest work is conducted all year round in unstructured terrain, which implies a high variation in temperature, humidity and visibility. Moreover, forest machines move and vibrate due to both the work they do and the movements of the machine through the rough terrain. In addition, the machine's engine makes the environment noisy. Since forestry work involves harvesting trees, the machine and its sensors are at risk of being hit by trees or branches. Finally, the forest environment is dirty; the machine will be exposed to soil, sawdust, rain, and possibly also snow, all of which may accumulate on its sensors. There are also two other factors that should be considered. First, the harvester head will typically be within 10 m of the machine because its position is limited by the reach of the crane. Second, forestry operations are cost sensitive, so any method used to monitor the head position must not greatly increase the cost of the work.

In most non forestry contexts, the most practical way of obtaining robust and high resolution data on the position of the manipulator is to use sensors that are physically attached to it. A wide range of suitable sensors of different prices and sizes are available. As a rule of thumb, more accurate sensors are more costly. A second factor to consider when mounting sensors on a manipulator relates to the extra hardware needed. For instance, external mounting often requires additional mechanical support, holders, screws, etc., which will probably have to be customized because the relevant components will not necessarily be commercially available. This may also be the case for any additional cabling and electronic devices required for data acquisition. In addition, real time data processing is required to achieve most of the benefits discussed in the preceding section. Therefore, fast computers are required.

In summary, an ideal method should be relatively economical, robust enough to tolerate harsh and varied forest conditions, and instantaneously provide accurate data.

3.2 Overview of methods

Methods for determining the location of a harvester head may be either local or global, depending on the location of the »base coordinate system« (CS). Local methods use a CS fixed to the harvester while global methods use a CS fixed to the ground. Methods can also be categorized according to the level of information they provide on the head's location. The full »pose« of an object in 3D is a set of six numbers defined relative to the chosen CS that specify the head's »position« in space and its »orientation«. The »orientation« or »attitude« is a set of three numbers describing the head's placement in terms of rotations around the three coordinate axes. The »position« is another set of three numbers that define the head's location in terms of translations or offsets along the coordinate axes.

Different applications may require different components of the full pose, which can be measured in either relative or absolute fashion. To identify a tree selected for harvesting on a map, it is typically sufficient to provide only the position of the harvester head with respect to the *x* and *y* axes (in global coordinates). In contrast, semi-autonomous control of a crane during harvesting operations requires the full pose, expressed relative to the harvester.

An overview of existing methods for local pose estimation is given below. The discussion is limited to local techniques because, in most cases relevant to harvesters, it is sufficient to know the pose relative to the machine. Furthermore, a local pose can be easily transformed into a global one if the global pose of the local CS is known. The methods presented are grouped into four different categories: »Angle and range-based methods« derive the pose by estimating the angles and/or ranges (distances) between a number of sensors and the harvester head. »Joint estimating methods« estimate the pose based on the geometry of the crane combined with direct measurements of joint angles and displacements. »Inertial techniques« use a combination of accelerometers, gyroscopes, and magnetometers, while »tilt sensors« estimate the static pose by sensing the head's orientation with respect to the earth's gravitational field.

3.3 Angle and range based methods

Poses can be estimated by measuring various angles, i.e. by triangulation. Wiklund et al. (1988) described the use of a rotating laser placed on the roof of an autonomous guided vehicle (AGV) to estimate the vehicle's pose by measuring the angles between the vehicle's long axis and assorted reflectors placed at known points in the environment. Alternatively, it is possible to have a similar system in which the fixed devices are the signal sources: Chunhan et al. (2003) used infra-red emitters placed at fixed positions and measured the incident angle of their emitted light on a sensor placed on the object whose position was to be determined.

One limitation of this approach is that it requires a clear line of sight to the harvester head. Given that the head rotates, this might be hard to achieve. Locating the reflectors on the boom tip could potentially solve this problem. However, even if the reflectors could always be pointed in the desired direction, the line of sight could be blocked by obstacles (e.g. trees, undergrowth, stones) or atmospheric conditions (e.g. fog, rain, snow or dust). Given a free line of sight to a visible reflector, triangulation should be able to determine the position of the head (relative to the harvester) with cm to dm accuracy.

Poses can also be estimated by various types of range estimations (trilateration). Satellite navigation systems such as GNSS utilize this approach to estimate global poses from »time of flight« data for radio signals broadcast simultaneously from several satellites. The GNSS receiver is placed on the object to be localized. Essential for this technique is exact time synchronization, which is achieved by using more satellites than would otherwise be necessary. Trilateration is also used in some local methods. Smith et al. (2004) presented a technique for indoor positioning that does not require synchronization. In this approach, range is estimated from »time of flight« data for ultrasonic pulses transmitted from beacons placed in the environment, and radio waves are used to synchronize transmission. It is also possible to place the ultrasonic transmitter on the object to be localized, as is done in the »Active Bat« location system (Harter et al. 1999). In such cases, the pose of the object is determined on the basis of signals picked up by several fixed receivers.

One potential solution based on this approach would be to simply equip the harvester head with a separate GNSS receiver. However, the resulting data would have the same limited accuracy as the GNSS positioning data for the machine. Thus, until better GNSS accuracy is achieved, it seems more suitable to estimate the harvester head's position relative to the machine.

If both angular and range data are available, a single measurement may be sufficient to specify the object's position. The object's position in Cartesian coordinates can be easily obtained by conversion from polar coordinates. Several types of sensors can be utilized to obtain combined angular and range measurements. For example, laser scanners emit laser beams and directly measure the angular coordinates and linear displacement of objects that reflect those beams into a 2D plane in front of the scanner. To determine the position of a specific object, it must be identified in the laser scan such that the relevant angle and range are determined. Depending on the type of laser used and the nature of the object, this may be quite challenging (for an example, see the section on field experiment 2).

Cameras can also be utilized as described by Davison and Kita (2002), who employed stereovision to detect a marker on the target object and thereby determine its 3D position and 2D orientation.

These methods require a (reasonably) clear line of sight and the ability to distinguish the desired object (i.e. the harvester head and/or the tree to be harvested) from other nearby objects. Provided that these conditions are satisfied, techniques such as laser scanning can provide very accurate (mm to cm) estimates of the harvester head's position relative to the machine. Camera based techniques are typically less accurate but should still be capable of providing data with a resolution of a few centimetres. Many of these methods offer a tradeoff between accuracy and data processing time. For instance, contemporary 3D lasers can provide high accuracy and high resolution data for easy object identification, but not (yet) in real time.

3.4 Joint estimating methods

The pose of an end effector can be estimated from joint values and the known geometry of the system on which the effector is mounted. The geometry can often be obtained with high accuracy from CAD/SolidWorks models, and various types of sensors can be attached to the system to monitor the rotational and translational motion of its individual joints. The resolution of an estimate obtained in this way is, according to the ISO 9283 standard, defined as the smallest incremental movement that can be sensed. For a serial manipulator of *N* joints, the resolution of the estimated end effector pose can be approximated as:

$$Resolution = \sum_{i=1}^{N} d_i(q) \times \delta q_i \qquad (1)$$

Where:

d_i distance between the end effector endpoint and rotational axis of the ith joint;

q vector of measured joint angles;

δq_i resolution of the ith sensor.

Consequently, the resolution is non linearly dependent on the joints and cannot be specified explicitly using a single value or range. A number of sensor types can be used to estimate joint angles; some that are widely used in robotics are discussed below.

3.4.1 Variable resistance joint sensors

Sensors containing variable resistors or voltage dividers measure the angle of rotation about a cylindrical joint or its displacement by exploiting the phenomenon of variable resistance: the voltage across the resistors in the sensor is proportional to the joint value. These sensors can be placed inside the cylinder, outside the cylinder, or at the joints. Examples are shown in Fig. 1.

When sensors are mounted on the cylinders, both the joint angles and the end effector position have to be estimated based on the geometry of the machine. The resolution of the measurement will depend on many factors, the most influential of which are the voltage range of the sensor and the number of bits in the Analog to Digital conversion (ADC). For example, only 1024 (2^{10}) different levels can be distinguished with a standard 10 bit ADC. A sensor with such an ADC, a 1 meter opening, and a voltage range of 0 to 5 volts would have a resolution of 4.88 mm according to the expression below:

$$Resolution = \frac{[Voltage\,range]}{2^{bits}} \times [cylinder\,maximum\,opening] \qquad (2)$$

Similarly, when the joint angle is being measured the resolution in radians can be calculated as:

$$Resolution = \frac{[Voltage\,range]}{2^{bits}} \times 2\pi \qquad (3)$$

3.4.2 Quadrature optical encoders

Most mechanical manipulators have encoders mounted on their joints to sense their angles of rotation (or displacement in the case of prismatic joints; see Fig. 2).

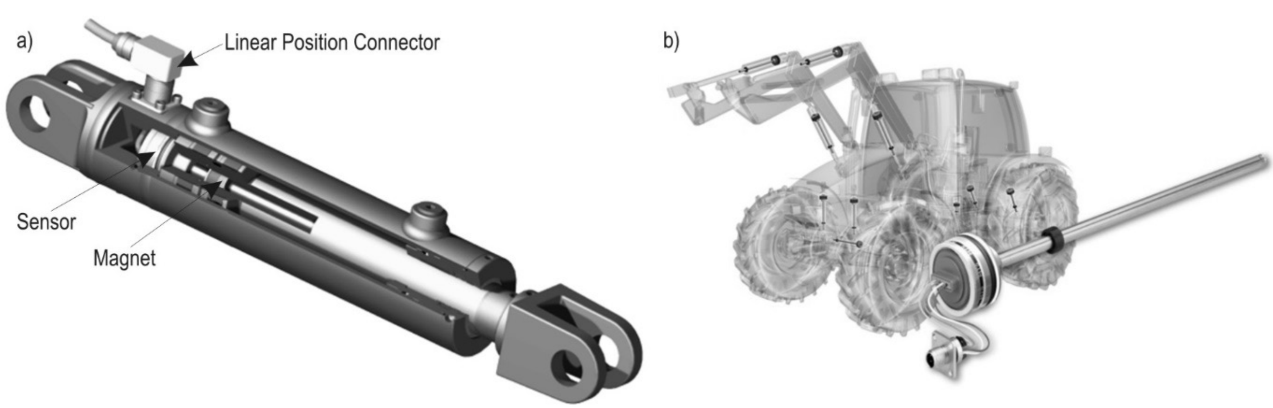

Fig. 1 Position sensing for hydraulic cylinders: a) A linear position sensor; b) Linear position sensor on a machine (source: www.texashydraulics.com)

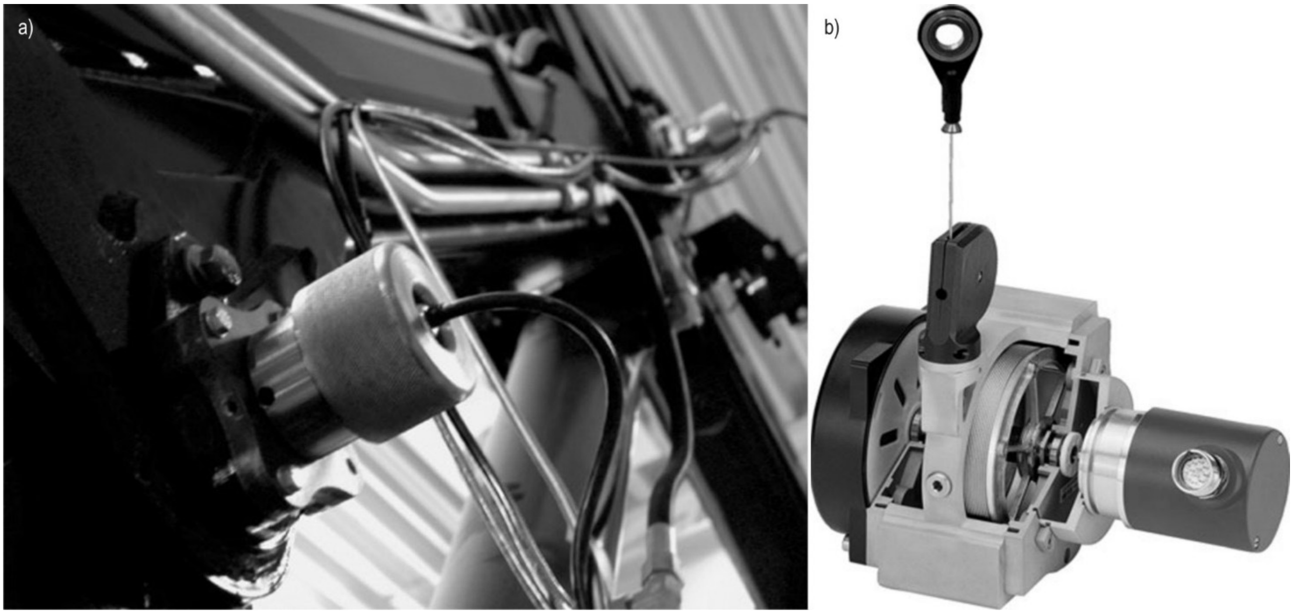

Fig. 2 Joint angle sensors with quadrature optical encoders: a) Encoder mounted on a joint; b) Rotary encoder with wire box for measuring linear motion (source: http://www.tfe.umu.se)

The resolution of optical encoders depends on the number of counts they perform per revolution. Assuming a resolution of N counts per revolution, the accuracy of the measurement is given by:

$$Resolution = \frac{1}{N} \times 2\pi \tag{4}$$

for rotary motion, and:

$$Resolution = \frac{1}{N} \times \left[maximum\, distance \right] \tag{5}$$

for linear motion.

For example, for a resolution of 5000 counts/revolution, we obtain an accuracy of 0.0012 radians. The accuracy in the measurement of the end effector position can then be estimated using Eq. 1.

Fig. 3 Optoelectronic absolute position monitoring system (source: http://www.parker.com)

3.4.3 Opto electronic joint sensors

Sensors of this kind are embedded in the joint's hydraulic cylinder (Fig. 3). A reading device is mounted on the head of the cylinder, which reads a pattern (barcode) on the piston rod. The pattern is recognized and the rod position determined by processing software. The pattern stamped on the piston rod is highly resistant to the effects of side loading, dust and rust. Such robustness makes this technology attractive for heavy duty machinery.

The accuracy of such sensors is usually given in their specifications, and their resolution typically varies from 0.03 mm to 0.25 mm. This is more than sufficiently accurate for most applications. However, it is important to recall that the resolution of the joint angles and end effector poses determined using sensors of this type is also dependent on the geometry of the machine.

3.4.4 Optical fibre goniometer

The technology used in fibre optic sensors for measuring joint angles was originally developed for the purposes of motion capture. It is therefore used extensively in biomechanics applications and the film industry. In recent years, the technology has matured and become more robust, leading to applications in more diverse contexts. Its wider uptake has been facilitated by its simplicity and low setup costs.

Electrogoniometers determine the angle of rotation about a cantilever joint by using a light sensor housed

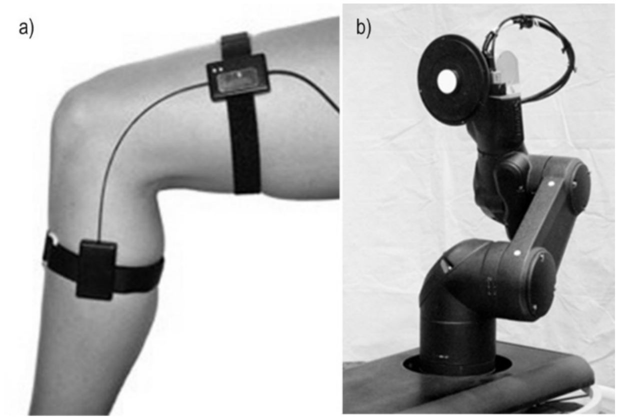

Fig. 4 Fibre optic electrogoniometer sensors: a) Joint angle electrogoniometer sensor; b) Manipulator with built in electrogoniometer sensors (source: http://www.adinstruments.com/)

in an enclosure to measure the amount of light passing through a pair of optic fibres running along the length of the cantilever (Fig. 4a). The resolution of the measurement device is typically specified by the product manufacturer, and usually varies from 0.01 to 0.1 degrees (0.000174 to 0.0017 radians).

Once again, the resolution for the ultimate measurement of the end effector position can be calculated using Eq. 1.

3.5 Inertial techniques and tilt sensors

Inertial measurement units (IMUs) are used for measuring velocity, orientation, and gravitational forces. Usually an IMU is a box containing sensors of three types; accelerometers, gyroscopes and magnetometers. In modern machine applications, IMUs are attached directly to the links in a rugged robust box, as shown in Fig. 5. To avoid the overhead of installing external cables, they are often wireless.

These kinds of IMUs are typically based on mechanical principles and are equipped with electronics that generate measurements in the form of electrical signals. Assuming the measuring device incorporates an ADC, the resolution of its measurements can be estimated using Eq. 2 and Eq. 3.

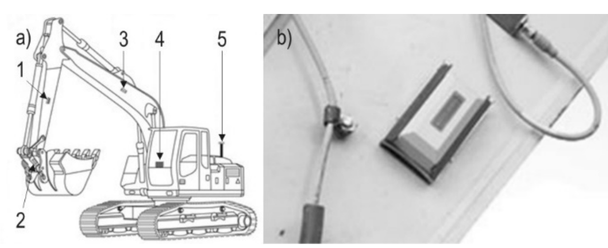

Fig. 5 Joint angle sensing on a machine fitted with IMUs: a) Placement of IMUs on an excavator; b) A ruggedized IMU (source: http://www.topconpositioning.com)

A problem often encountered using IMUs is that, while velocity and acceleration are reliably measured, it is difficult to obtain reliable positional information. This is because environmental factors (e.g. the presence of nearby metals, magnetic fields, radio signals, etc.) may cause the output of the magnetometers to fluctuate. Additional software estimation is required to cope with this problem. Observer based estimation techniques, such as Kalman filtering, are used to combine the information from the accelerometers and gyroscopes of the IMU and obtain statistically optimal estimates of the system's 3D position and angular orientation. Using these data and simple geometrical relationships, it is possible to estimate the pose of the end effector. It is difficult to quantify the resolution of these measurements because it depends on the software that is used. Algorithmic estimation can be very accurate, regardless of the sensor resolution, because it is under the programmer's control. This is the main reason why IMU technology has been widely used for wireless sensing in diverse industries including motion capture, biomedicine, unmanned aerial vehicles and robotics.

4. Matching benefits to methods for estimating the location of the harvester head

The accuracy required to realize a particular benefit is not by itself sufficient to determine which sensing technologies are best suited to deliver that benefit. More important criteria are the time constraints and the number of positions at which sensors are required. Therefore, we briefly outline the anticipated positioning process and then present a matching matrix that compares the various benefits achievable with head positioning data to the methods of acquiring such data.

4.1 The positioning process

Different applications have different positional information requirements. In general, either point or continuous estimates are needed. Point estimates provide information on the position of the harvester head at specific points in time; they are useful in cases where it is necessary to know the position of a harvested tree, for example. Most indirect applications (e.g. those associated with ecological mapping) require point estimates. Conversely, direct benefits such

Table 1 Potential for the implementation of different position sensing methods, and the fit between each method's accuracy and that required to realize specific benefits

Method	Implementation potential	Benefit							
		3D forest mapping	Training of ALS	Timber traceability	Product features	Density of tree removals	Virtual marking and constraining	Machine (semi) automation	Improving work methods
Angle and/or range	0	+	+	++	++	++	++	--	0
Joint sensors	++	++	++	++	++	++	++	0	++
Tilt sensors	+	++	++	++	++	++	++	0	++
IMU	++	++	++	++	++	++	++	0	++

Note:
++ – highly likely to be implemented/much higher accuracy than needed;
+ – likely to be implemented/higher accuracy than needed;
0 – might be implemented/acceptable accuracy;
- – unlikely to be implemented/less accuracy than needed;
-- – very unlikely to be implemented/much less accuracy than needed.

as those associated with mapping and controlling machine movements require a continuous flow of information on the location of the head. In automation applications this flow must be supplied in real time, which inevitably requires high processing capacity.

Point estimates present less of a challenge but require precise control over which positions are estimated. This can be achieved by connecting the estimation process to specific machine commands. During harvesting, the harvester head grasps the tree when it is felled. Therefore, if the location and the direction of a point on the harvester head are known, the position of the tree's centre can be determined. The estimation of the head's position (and thus the tree's position) can be synchronized with the action of cutting the tree, during which the harvester head is held still for a second or two to enable the chainsaw to cut through the stem. In this case, the harvester head would be in the desired location during the few seconds between being moved towards the tree and the point at which the tree starts to fall. Once the tree is felled, the harvester head and tree are moved to enable subsequently cut logs to fall into separate assortment piles. The position measurements must, therefore, be acquired quickly because the head spends relatively little time in the desired position, and there is typically only 30 seconds or so between tree fellings. Moreover, once a given tree's position has been determined, it must be saved and linked to each of the logs that are subsequently cut from the tree (together with information on the tree's length, taper, species, and so on). The entire process must then be repeated when the next tree is felled.

4.2 Matching matrix

To systemize the matching of benefits and sensing methods, we have constructed a matrix showing how suitable we consider different methods to be for the realization of specific benefits, assuming that the accuracy of the positional data depends only on the accuracy with which the position of the head is estimated relative to the machine (Table 1). This approach is adopted because we expect that the accuracy of global positioning data for machines will increase substantially in the near future. We also give our opinions on the likelihood that the different methods will be commercialized. For the sake of simplicity, we classify the methods and benefits using a five level scale, and present both in rather general terms. Nevertheless, the matrix clearly shows that there are a range of viable methods that could be used to realize most of the benefits. It also indicates that the methods that are most likely to be implemented commercially, i.e. those based on crane joint position sensors or IMUs, are capable of meeting the requirements of most benefits (Table 1).

5. Field experiment 1 – a 2D laser scanner mounted on a harvester cabin

An alternative to trying to localize the harvester head is to determine the position of the tree that was just harvested. The first step in implementing such a method is to identify a practical way of creating a local map of the trees surrounding the harvester. When a tree is harvested, we should be able to detect which tree is missing from this map. The reliability of this tree detection process can be improved by accurate estimations of tree diameter. In this section, we describe two different field experiments using a SICK LMS 221 2D laser scanner to detect trees. The angular resolution of a single laser beam emitted by the scanner was 0.25° and its field of view is 100°. Each scan consisted of 401 beams. According to the manufacturer, the laser scanner had a measurement range of up to 80 m, and a measurement accuracy of ±3.5 cm for ranges up to 20 m. However, to take advantage of this high accuracy, trees must be distinguished from other objects (e.g. brush, branches, rocks, etc.). Therefore, a key goal of the study was to evaluate the utility of data collected using a 2D laser mounted on a harvester.

In the first experiment (Hellström et al. 2012), the laser scanner was mounted on top of a harvester cabin. Measurements were acquired at three different locations in the same forest, with varying degrees of visual obstruction due to branches, leaves, needles, and so on. To identify trees from laser scanning data, the first thing that must be done is to cluster the laser points. This was done using an algorithm developed by Jutila et al. (2007) with minor modifications. To validate the clusters, the estimated diameter of each tree cluster has to be calculated and checked to ensure that it is within a reasonable range (between 15 and 80 cm in our study). We implemented and tested the accuracy of several different methods for calculating tree diameters from clusters in the laser scanning data.

The tree identification algorithm was found to work reasonably well even at a forest site with quite severe visual obstruction due to branches and needles. However, a tree that was identified in one laser scan was not always detected in the next even though the scanner was not moved between scans. It also failed to detect all trees. Some trees were blocked by the harvester crane and some were blocked by other trees or branches. Several methods for enhancing tree detection were evaluated, such as using median values from several consecutive scans. Overall, however, it was concluded that 2D laser scanners are not suitable or reliable for detecting recently harvested trees due to uncertainties in tree detection efficiency. However, the detected trees did appear to have been positioned with at least cm level accuracy (although this was not investigated rigorously).

Another possible use for this tree detection method is to localize the vehicle relative to the surrounding trees. By generating a local tree map and matching it with a global map, which could be generated from ALS data, the machine's position can be determined more exactly than would be possible by using a GNSS (Rossman et.al 2010), which has obvious limitations in dense forests. In this scenario, it is not necessary to find all trees (or a specific one); we need only find enough trees to allow the accurate matching of local and global maps.

The results obtained using different methods for estimating tree diameter varied considerably between the three experimental sites and also between methods. The average error for the different methods varied between 40% and 90%. No method was best for all circumstances. Since estimated diameters are used to validate identified tree clusters, a more accurate diameter estimation method should increase the number of trees identified in a given laser scan and thus make it easier to filter out clusters that do not correspond to trees. To develop better methods for diameter estimation, we conducted a second experiment indoors (Ringdahl et al. 2013) using nine tree trunk sections with diameters of 6–50 cm. The tree sections were placed one at a time in an indoor corridor, at distances varying between 5 and 20 meters, with different sides facing the laser scanner. In total, we measured 172 combinations of stem section diameters and distances. For each measurement, the tree's real diameter was manually measured with mm accuracy using a caliper at the spot where the laser beams hit. The same clustering algorithm as described above was used to identify trees in the laser scan. However, since there was only one tree in each scan, there was no need for validation of the clustering.

The algorithms for diameter estimation evaluated in the previous experiment were used again in this study. We also developed enhanced algorithms that compensate for the effect of the beam width and rely on multiple scans. The best existing algorithms overestimated the tree trunk diameters by ca. 40%. Our enhanced algorithms reduced this error to less than 12%.

The tested 2D laser scanner thus proved to be unsuitable for estimating the positions of either harvested trees or the harvester head. However, its output may be useful in improving the accuracy with which the machine's position is determined, thereby increasing the accuracy of other methods for estimating the head position relative to the machine.

6. Field experiment 2 – encoders on crane joints

A very reliable method used for estimating the boom tip coordinates of forestry cranes is to monitor

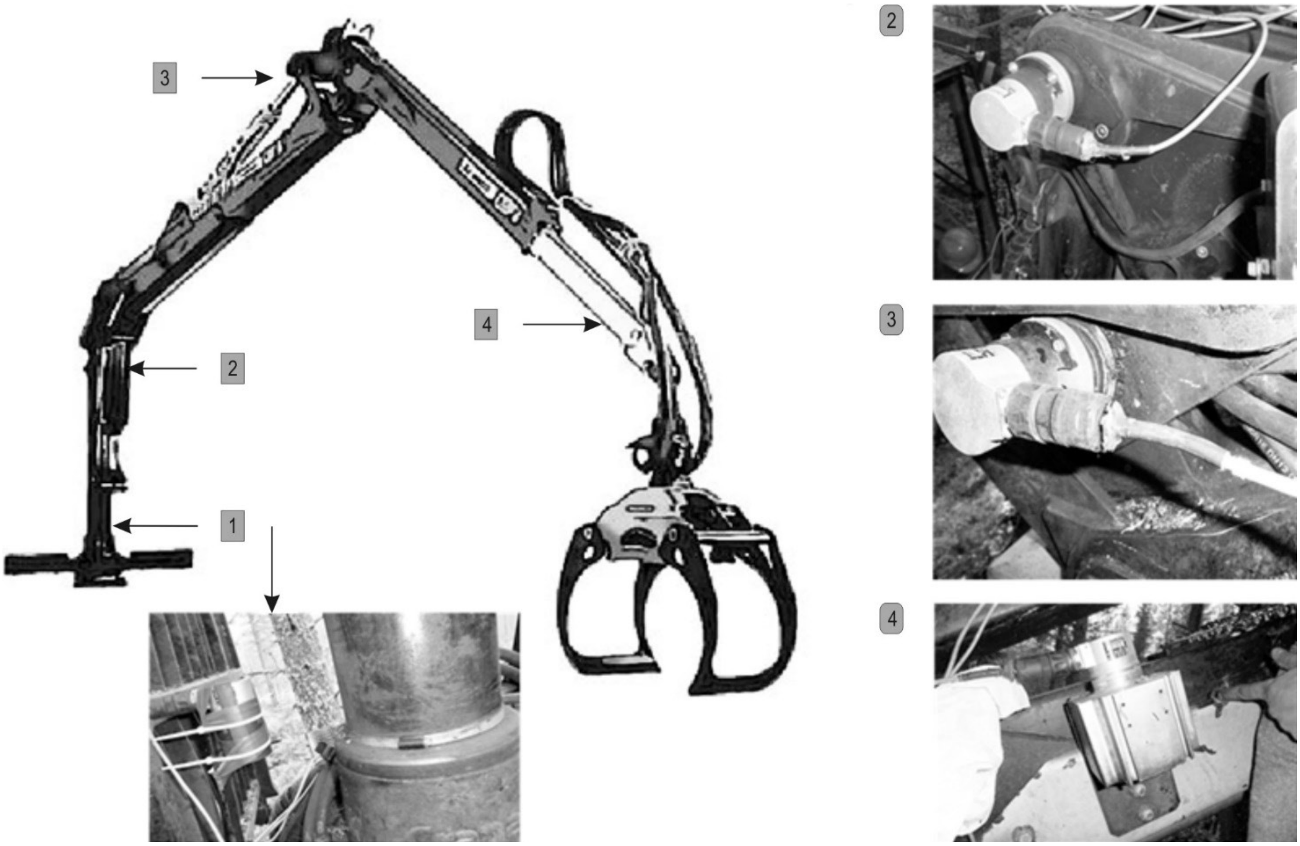

Fig. 6 Forwarder crane with sensors attached at the joint level for measuring angular motion. This experimental platform has been operating for more than a decade. During this time the sensors have never been changed. Based on this demonstration of the sensing device's reliability and robustness, a commercial version of this solution has been developed (Cranab 2013b)

the angular motion of their joints. Below we present some results from a decade long series of studies (Ortiz Morales et al. 2014, Westerberg 2014), whose results contributed to the development and recent release of a commercial product (Cranab 2013b). The aim of this discussion is to illustrate the practicality of this approach to gathering data on the positions of crane booms. Previous studies (Westerberg 2014) have shown that the method's accuracy is high enough to support crane automation; using a similar approach to that embodied in Eq. 1, it was determined to be of mm level (Daniel Ortíz et al. 2014).

A Komatsu 830.3 forwarder (Komatsu Forest 2013) was used in the study. The forwarder was equipped with a CRANAB CRF 5.1 crane (Cranab 2013a), which has a reach of 9.3 m. The grapple used was a Komatsu G28, with an Indexator G121 rotator (Indexator 2013).

During the experiments, the machine was equipped with four sensors to measure its joint angles and the telescopic displacement (Fig. 6). These sensors were quadrature encoders (Heidenhain, ROD 426–5000) with a resolution of 5000 pulses per revolution. As such, they provide a measuring accuracy of 0.072 degrees (0.0012 rad) for the angular joints and 0.0007 m (0.7 mm) for the telescope. The crane was also fitted with a real time data acquisition unit that can record incoming signals at a frequency of 1 KHz (1000 recordings every second).

The sensing system was used to study the working patterns of experienced forwarder operators. To this end, a group of five professional operators were asked to use the machine in their normal working routine. Since the only additions to the machine are the sensors, the operators were free to use its standard computer to tune the machine settings to their liking. Positional data were recorded over the course of a week of scheduled working time for each operator.

The measurements provided by the joint sensors represent angular movement in radians, and displacement in meters in the case of the telescopic link. These quantities are recorded using the coordinate system sketched in Fig. 7.

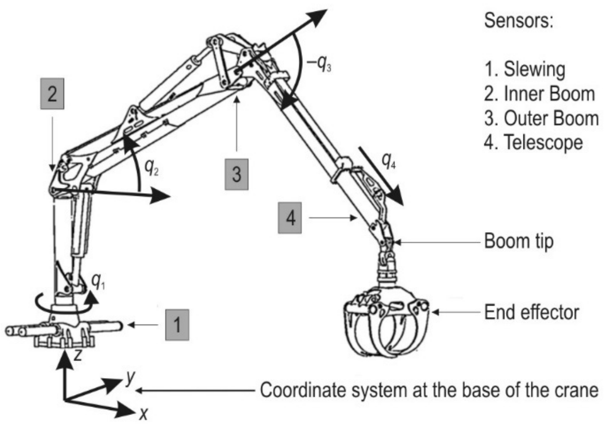

Fig. 7 Forwarder crane coordinate system and generalized joint coordinates

After processing the data, a reconstruction of the boom-tip's motion was generated by considering the kinematic geometry of the machine (Fig. 8). The results clearly indicate that it is possible to fit standard forest cranes with joint estimating sensors that can withstand the challenges of forestry operations. Moreover, it also clearly shows the potential benefit of having the capacity to analyze and visualize crane work (Fig. 8). Indeed, this kind of visualization is likely to substantially improve the analysis and evaluation of experienced operators' working methods, and the training of new operators (Daniel Ortíz et al. 2015).

7. Discussion

Our analysis highlights the joint estimating principle and IMUs as the methods with the greatest potential for implementation. Both satisfy the accuracy requirements for all of the benefits that could potentially be realized using positional data for harvester heads. The practical potential of these technologies is demonstrated by the fact that two leading forestry companies have presented solutions incorporating them since the initiation of this project. John Deere uses sensors in its Intelligent Boom Control solution to enable boom tip control, and to generate feedback on certain aspects of the working process such as the frequency at which trees are moved from one side of the machine to another (John Deere 2013). Similarly, Cranab uses sensors to provide information about the position of the crane boom relative to the machine (Cranab 2013b). As indicated in the analyses, many sensing methods could potentially be used but are less robust or well suited to heavy duty forest work. The ongoing development of recently introduced products for positioning the harvester head (i.e. boom tip) will enable the realization of most of the benefits discussed herein if end users wish to do so. However, the realization of some benefits (particularly Timber traceability and improved classification of product properties) will require the development of cost efficient methods for linking information about individual logs from different stages in the forest value chain.

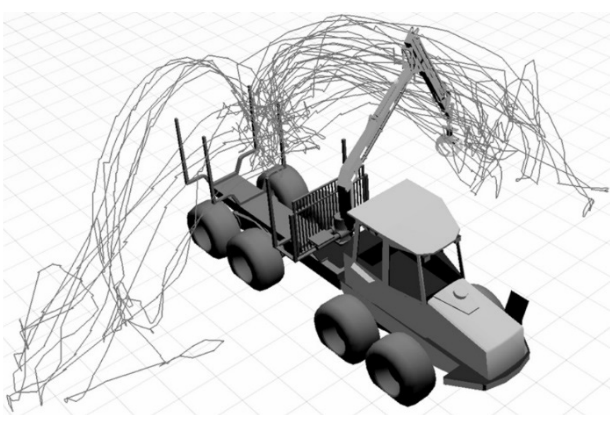

Fig. 8 Calculated boom tip movement patterns based on recordings of the joint angles and telescopic opening

To accurately determine the harvester head's position, we chose to focus on the positioning of the harvester head relative to the forest machine. However, during the analysis it was noted that the interactions between certain methods offered opportunities to simultaneously estimate local and global positioning. Based on these findings, we believe that combined local and global approaches will ultimately be adopted to improve the accuracy of both. However, some of the benefits considered in this work will not gain from high global accuracy. For instance, the benefit that has the most stringent requirements in terms of relative accuracy, i.e. machine (semi) automation, is completely independent of the machine's global position. In contrast, ecological mapping benefits require global accuracy. However, the required level of local accuracy (i.e. accuracy in determining the head's position relative to the machine) for ecological mapping is much lower than that for (semi) automation. In the end, high accuracy in both global and local positioning will always be useful, as long as it does not come at too high a price.

Naturally, this kind of study cannot cover all of the potential benefits that may be realized by accurately measuring the position of the harvester head or a forest machine's boom tip; similarly, it would be impossible to discuss all of the methods that could be used to acquire such data. Indeed, this overview is already lengthy enough. However, we hope that by highlighting some of these benefits and promising positioning methods, we will introduce a wider audience to the potential of this recent technical development. In future, we look forward to building on the results and ideas presented herein by examining new solutions for realizing some of the prospective benefits arising from having detailed information on the location of the harvester head.

Acknowledgements

This work was funded by the Royal Swedish Academy of Agriculture and Forestry (KSLA; H11-0085-MEK, H11-0085-GBN). We would like to thank Sees-Editing Ltd for revising the English language.

8. References

Alam, M.M., Strandgard, M.N., Brown M.W., Fox, J.C., 2012: Improving the productivity of mechanised harvesting systems using remote sensing. Australian Forestry 75(4): 238–245.

Andersen, H.E., Clarkin, T., Winterberger, K., Strunk, J., 2009: An accuracy assessment of positions obtained using survey and recreational grade global positioning system receivers across a range of forest conditions within the Tanana Valley of interior Alaska. Western Journal of Applied Forestry 24(3): 128–136.

Anon., 2010: StanForD 2010 – modern communication with forest machines. Uppsala, Sweden, Skogforsk. 16 p.

Arii, K., Caspersen, J.P., Jones, T.A., Thomas, S.C., 2008: A selection harvesting algorithm for use in spatially explicit individual based forest simulation models. Ecological modelling 211(3): 251–266.

Arshadi, M., Backlund, I., Geladi, P., Bergsten, U., 2013: Comparison of fatty and resin acid composition in boreal lodgepole pine and Scots pine for biorefinery applications. Industrial Crops and Products 49: 535–541.

Athanasiadis, I.N., Anastasiadou, D., Koulinas, K., Kiourtsis, F., 2013: Identifying Smart Solutions for Fighting Illegal Logging and Timber Trade. In Environmental Software Systems. Fostering Information Sharing, Springer, Berlin Heidelberg 143–153 p.

Barth, A., Holmgren, J., 2013: Stem taper estimates based on airborne laser scanning and cut-to-length harvester measurements for pre-harvest planning. International Journal of Forest Engineering 24(3): 161–169.

Berg, S., Bergström, D. Nordfjell, T., 2014: Simulating conventional and integrated stump and round wood harvesting systems: a comparison of productivity and costs. International Journal of Forest Engineering 25(2): 138–155.

Bollandsås, O.M., Maltamo, M., Gobakken, T., Lien, V., Naesset, E., 2011: Prediction of Timber Quality Parameters of Forest Stands by Means of Small Footprint Airborne Laser Scanner Data. International Journal of Forest Engineering 22(1): 14–23.

Chunhan, L., Yushin, C., Gunhong, P., Jaeheon, R., Seung-Gweon, J., Seokhyun, P., Jae, W.P., Hee, C.L., Keum-Shik, H., Man, H.L., 2004: Indoor positioning system based on incident angles of infrared emitters Industrial Electronics Society. IECON, 30th Annual Conference of IEEE (Vol. 3).

Cranab 2013a: Cranab - Products - Forwarder Cranes. Available at: http://www.cranab.info/www%5Ccranabcom.nsf/pages/ProductsForwarderCranes.

Cranab 2013b: Cranab presents an entirely new generation of cranes. Available at: http://www.cranab.se/static/en/206/.

Davison, A.J., Kita, N., 2002: Active Visual Localization for Multiple Inspection Robots. Advanced Robotics 16(3): 281–295.

Dissanayake, M.W.M.G., Newman, P., Clark, S., Durrant-Whyte, H., Csorba, M.A., 2001: Solution to the simultaneous localization and map building (SLAM) problem. IEEE Trans. Robot. Autom. 17(3): 229–241.

Eriksson, D., Lindberg, H., Bergsten, U., 2006: Influence of silvicultural regime on wood structure characteristics and mechanical properties of clear wood in *Pinus sylvestris*. Silva Fennica 40(4): 743–762.

Eriksson, M., Lindroos, O., 2014: Productivity of harvesters and forwarders in CTL operations in Northern Sweden based on large follow-up datasets. International Journal of Forest Engineering 25(3):179–200.

Fortin, M., Delisle-Boulianne, S., Pothier, D., 2013: Considering spatial correlations between binary response variables in forestry: an example applied to tree harvest modeling. Forest Science 59(3): 253–260.

Gellerstedt, S., 2002: Operation of the single-grip harvester: motor-sensory and cognitive work. International Journal of Forest Engineering 13(2): 35–47.

Hakli, J., Jaakkola, K., Pursula, P., Huusko, M., Nummila, K., 2010: UHF RFID based tracking of logs in the forest industry. IEEE International Conference on RFID. Orlando, FL, USA, 14–16 April, 245–251.

Harter, A., Hopper, A., Steggles, P., Ward, A., Webster, P., 1999: The Anatomy of a Context Aware Application. In Proc. 5th ACM MOBICOM Conf. Seattle, WA.

Heidenhain, 2013: Measurement and Control Technology for Demanding Positioning Tasks. Available at: http://www.heidenhain.de/de_EN/home/.

Hellström, T., Lärkeryd, P., Nordfjell, T., Ringdahl, O., 2009: Autonomous Forest Vehicles: Historic, envisioned, and state-of-the-art. International Journal of Forest Engineering 20(1): 31–38.

Hellström, T., Ringdahl, O., 2009: Real time path planning using a simulator-in-the-loop. International Journal of Vehicle Autonomous Systems 7(1/2): 56–72.

Hellström, T., Hohnloser, P., Ringdahl, O., 2012: Tree diameter estimation using laser scanner. Technical Report UMINF 12.20, Department of Computing Science, Umeå University, Umeå, Sweden.

Holmgren, J., Barth, A., Larsson, H., Olsson, H., 2012: Prediction of stem attributes by combining airborne laser scanning and measurements from harvesters. Silva Fennica 46(2): 227–239.

Huang, S., Wang, Z., Dissanayake, G., 2008: Sparse local submap joining filter for building large-scale maps. IEEE Trans. Robot. 24(5): 1121–1130.

Hyyppa, J., Hyyppa, H., Leckie, D., Gougeon, F., Yu, X., Maltamo, M., 2008: Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. Int. J. Remote Sens. 29(5): 1339–1366.

Indexator, 2013: Rotators and accessories – Indexator. Available at: http://www.indexator.se/en/rotator_systems/rotators_and_accessories.

John Deere, 2013: Intelligent Boom Control (IBC). Available at: http://www.deere.co.uk/wps/dcom/en_GB/industry/forestry/learn_more/ibc_en.page.

Jutila, J., Kannas, K., Visala, A., 2007: Tree Measurement in Forest by 2D Laser Scanning. International Symposium on Computational Intelligence in Robotics and Automation. IEEE, 491–496.

Komatsu Forest, 2013: 830.3 – Sverige – Komatsu Forest . Available at: http://www.komatsuforest.se/default.aspx?id=10876.

Lee, C., Chang, Y., Park, G,. Ryu, J., Jeong, S.G., Park, S., Park, J.W., Lee, H.C., Hong, K.S., Lee, M.H., 2004: Indoor positioning system based on incident angles of infrared emitters. Industrial Electronics Society. IECON 2004. 30th Annual Conference of IEEE, vol. 3: 2218–2222.

Lindroos, O., 2012: Evaluation of technical and organizational approaches for directly loading logs in mechanized CTL harvesting. Forest Science 58(4): 326–341.

Mettin, U., La Hera, P.X., Morales, D.O., Shiriaev, A.S., Freidovich, L.B., Westerberg, S., 2009: Path-constrained trajectory planning and time-independent motion control: Application to a forestry crane. In Proceedings of 14th International Conference on Advanced Robotics (ICAR).

Miettinen, M., Ohman, M., Visala, A., Forsman, P., 2007: Simultaneous Localization and Mapping for Forest Harvesters. In Proceedings of the 2007 IEEE International Conference on Robotics and Automation. 10–14 April, Roma, Italy: 517–522.

Milne, B., Chen, X.Q., Hann, C.E., Parker, R., 2013: Robotisation of forestry harvesting in New Zealand – An overview. The 10th IEEE International Conference on Control and Automation (ICCA), 12-14 Jun, Hangzhou, China, 1609–1614.

Möller, J.J., Bhuiyan, N., Hannrup, B., 2012: Monitoring of thinning using harvester data. Resultat 1, Uppsala, Sweden, Skogforsk.

Murphy, G., 2014: Priority list bucking on a mechanized harvester considering external properties and stiffness of Douglas-fir. International Journal of Forest Engineering 25(3): 214–221.

Murphy, G., Clark, J.A., Pilkerton, S., 2012: Current and Potential Tagging and Tracking Systems for Logs Harvested from Pacific Northwest Forests. Western Journal of Applied Forestry 27(2): 84–91.

Naesset, E., Jonmeister, T., 2002: Assessing point accuracy of DGPS under forest canopy before data acquisition, in the field and after postprocessing. Scandinavian Journal of Forest Research 17(4): 351–358.

Næsset, E., Gobakken, T., Holmgren, J., Hyyppä, H., Hyyppä, J., Maltamo, M., Nilsson, M., Olsson, H.K., Persson, A.S., Söderman, U., 2004: Laser scanning of forest resources: The nordic experience. Scand. J. For. Res. 19(6): 482–499.

Nordström, M., Wilhelmsson, L., Arlinger, J., Möller, J.J., 2010: Harvester data can provide important advance information to end users. Resultat 21, Uppsala, Sweden, Skogforsk.

Ortiz Morales, D., Westerberg, S., La Hera, P.X., Mettin, U., Freidovich, L., Shiriaev, A.S., 2014: Increasing the Level of Automation in the Forestry Logging Process with Crane Trajectory Planning and Control. Journal of Field Robotics, 31(3): 343–363. doi: 10.1002/rob.21496.

Ortiz Morales, D., La Hera, P., Westerberg, S., Mettin, U., Freidovich, L., Shiriaev, A., 2015: Path-constrained motion analysis. An algorithm to understand human performance on hydraulic manipulators. IEEE Transactions Journal on Human-Machine Systems 45(2): 187–199.

Ovaskainen, H., Heikkilä, M., 2007: Visuospatial cognitive abilities in cut-to-length single-grip timber harvester work. International Journal of Industrial Ergonomics 37(9): 771–780.

Persson, 1977: Quality development in young spacing trials with Scots pine. Swedish University of Agricultural Science, Department of Forest Yield Research, Report 45, 152 p.

Purfürst, T., Lindroos, O., 2011: The long-term productivity's correlation with subjective and objective ratings of harvester operators. Croatian Journal of Forest Engineering 32(2): 509–519.

Ringdahl, O., 2011: Automation in Forestry – Development of Unmanned Forwarders. PhD thesis, Department of Computing Science, Umeå University.

Ringdahl, O., Hohnloser, P., Hellström, T., Holmgren, J., Lindroos, O., 2013: Enhanced Algorithms for Estimating Tree Trunk Diameter Using 2D Laser Scanner. Remote Sensing 5(10): 4839–4856.

Rodríguez-Pérez, J.R., Álvarez, M., Sanz-Ablanedo, E., 2007: Assessment of low-cost GPS receiver accuracy and precision in forest environments. Journal of Surveying Engineering 133(4): 159–167.

Rossmann, J., Krahwinkler, P., Schlette, C., 2010: Navigation of mobile robots in natural environments: Using sensor fusion in forestry. J. Syst. Cybern. Inform. 8(3): 67–71.

Rossmann, J., Schluse, M., Waspe, R., Moshammer, R., 2011: Simulation in the woods: from remote sensing based data acquisition and processing to various simulation applications. In: Proceedings of the 2011 Winter Simulation Conference »Simulation for a Sustainable World« edited by S. Jain, R. R. Creasey, J. Himmelspach, K. P. White, and M. Fu, December 11–14, Phoenix, Arizona, 984–996.

Rossmann, J., Schluse, M., Schlette, C., Buecken, A., Krahwinkler, P., Emde, M., 2009: Realization of a highly accurate mobile robot system for multi purpose precision forestry applications. The 14th International Conference on Advanced Robotics, 22–26 June, Munich, 1–6.

Seidel, F., Fripp, E., Adams, A., Denty, I., 2012: Tracking Sustainability. Review of Electronic and Semi-Electronic Timber Tracking Technologies. ITTO Technical Series TS-40. The International Tropical Timber Organization (ITTO), Yokohama, Japan. 62 p.

Shiriaev, A., Freidovich, L., Manchester, I., Mettin, U., La Hera, P., Westerberg, S., 2008: Status of Smart Crane Lab Project: Modeling and Control for a Forwarder Crane; Technical Report; Department of Applied Physics and Electronics, Umeå University: Umeå, Sweden.

Smith, A., Balakrishnan, H., Goraczko, M., Priyantha, N.B., 2004: Tracking Moving Devices with the Cricket Location System, in Proc. of The 2nd Int. Conf. on Mobile Systems, Applications and Services.

Stendahl, J., Dahlin, B., 2002: Possibilities for harvester-based forest inventory in thinnings. Scandinavian Journal of Forest Research 17(6): 548–555.

Thorpe, H.C., Vanderwel, M.C., Fuller, M.M., Thomas, S.C., Caspersen, J.P., 2010: Modelling stand development after partial harvests: An empirically based, spatially explicit analysis for lowland black spruce. Ecological Modelling 221(2): 256–267.

Yang, K.C., 2002: Impact of spacing on juvenile wood and mature wood properties of white spruce (*Picea glauca*). Taiwan Journal of Forest Science 17(1): 13–29.

Zheng, Y., Liu, J., Wang, D., Yang, R., 2012: Laser scanning measurements on trees for logging harvesting operations. Sensors 12(7): 9273–9285.

Wang, Z., Huang, S., Dissanayake, G., 2005: D-SLAM: Decoupled localization and mapping for autonomous robots. In Proceedings of the International Symposium of Robotics Research, ISRR 05, San Francisco, CA, USA, 12–15 October (Vol. 26): 203–213.

Westerberg, S., 2014: Semi-automating forest machines. Motion planning, system integration and Human-Machine interactions. PhD thesis, Dep. Applied Physics and Electronics, Umeå University, Sweden.

Wiklund, U., Andersson, U., Hyyppä, K., 1988: AGV navigation by angle measurements. Proc. 6th int. Conf. Automated Guided Vehicle System, Brussels, October, 199–212.

Öhman, M., Miettinen, M., Kannas, K., Jutila, J., Visala, A., Forsman, P., 2008: Tree Measurement and Simultaneous Localization and Mapping System for Forest Harvesters. In Laugier, C. and Siegwart, R., Field and Service Robotics. Springer, Berlin Heidelberg, 369–378.

Received: September 3, 2014
Accepted: January 9, 2015

Authors' address:

Assoc. Prof. Ola Lindroos, PhD.*
e-mail: ola.lindroos@slu.se
Pedro La Hera, PhD.
e-mail: xavier.lahera@slu.se
Department of Forest Biomaterials and Technology
Swedish University of Agricultural Sciences
SE-901 83 Umeå
SWEDEN

Ola Ringdahl, PhD.
e-mail: ringdahl@cs.umu.se
Peter Hohnloser
e-mail: peterh@cs.umu.se
Assoc. Prof. Thomas Hellström, PhD.
e-mail: thomash@cs.umu.se
Department of Computing Science
Umeå University
SE-901 87 Umeå
SWEDEN

* Corresponding author