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Simultaneous Localization and Mapping for Forest Harvesters

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Abstract— **A real-time SLAM (simultaneous localization and mapping) approach to harvester localization and tree map generation in forest environments is presented in this paper. The method combines 2D laser localization and mapping with GPS information to form global tree maps. Building an incremental map while also using it for localization is the only way a mobile robot can navigate in large outdoor environments. Until recently SLAM has only been confined to small-scale, mostly indoor, environments. We try to addresses the issues of scale for practical implementations of SLAM in extensive outdoor environments. Presented algorithms are tested in real outdoor environments using an all-terrain vehicle equipped with the navigation sensors and a DGPS receiver.**

I. Introduction

AUTONOMOUS localization and mapping capabilities are widely accepted to be one of the key features of outdoor mobile robots. For this reason robot navigation has been an ongoing research topic for several years. Navigation in outdoor environments is still an open problem. The presence of unstructured features leads to the need for more complex perception and modeling. This leads to a big variety of navigation algorithms and map representations, depending on the kind of environment, the degree of structuring and the target application. Many different outdoor SLAM algorithms have been studied in recent years (for a review see [4],[13] and the references therein). The two critical research subjects especially related to mapping of large environments are data association and controlling computational complexity.

Data association is the problem of relating sensor measurements with the corresponding elements in the map. There are two basic approaches for solving the data association problem [7]. In the first one a set of potential vehicle location candidates are generated for computing the correlation match between sensor measurements and the previous map [2]. In the second approach, discrete features are extracted from the sensor measurements to be matched with the similar features stored in the map. This approach is used in the feature based, Extended-Kalman-Filter (EKF) SLAM implementations [9],[16],[5]. When mapping large outdoor environments uncertainty in the vehicle location may increase to the extent that correct localization based on one-to-one feature correspondences is not possible [14]. A more robust data association method relies on joint compatibility of a set of geometric constraints computed among neighboring features [6],[7],[14]. In constructing a 3D map of a cluttered forest environment exhausted search in the pose space for vehicle relocation has been demonstrated to yield good results [11]. However, the method becomes computationally heavy for a real-time implementation when the vehicle error increases too much between observation phases. In the method presented in this paper the data association problem is solved by considering a neighborhood of each tree for computing a set of relative geometric constraints among the trees in the current vehicle centered map and the global map. By checking the joint consistency among the constraint sets an observed tree can be reliably associated with a tree in the map despite the cluttered environment.

The computational complexity of standard EKF-SLAM is proportional to the square of the number of landmarks in the map. Different approaches to augment the basic method to achieve real-time performance have been proposed. By working on a limited area of the global map at a time, the total computational cost of the method can be made proportional to the number of landmarks [5]. By applying a relative sub map framework the computational cost at the local sub map level will be independent of the size of the complete map. Moreover, the precision of the map can be increased due to the increased consistency when closing long loops [1].

Laser scanners have become one of the most attractive sensors for localization and map building purposes due to their accuracy and low cost. Most common lasers provide range and bearing information with sub degree resolution and accuracies of the order of 1-10 cm in 10-50 meter ranges [3], [9], [16].

The Forestrix project studies forest and tree trunk measurement technologies, signal processing methods and algorithms for semiautomatic control of forest harvesters. Advances in laser range finders and machine vision systems provide new opportunities for forest measurements. An accurate tree map can be formed and updated in real-time. In

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thinning of a forest the tree map can support the harvester operator to select the right trees and to achieve optimal stand density. The stand density can be broadly defined as the quantitative measure of tree cover on an area, i.e. the amount of tree material per unit area or space [15]. The collected data improves the verifiability of forest operations. Later the data can be used for planning the subsequent forest operations [8], [10].

In the first phase of the project, measurement technologies and signal processing methods are tested on an all-terrain vehicle (ATV) which is a small 4-wheeled motorized buggy. The ATV is equipped with a mobile data collection system. It is used to collect real measurement data from various forest environments. The signal processing methods are then studied and developed based on the data in laboratory environment. Thereafter, the developed algorithms are tested on the ATV platform at which they should run in real-time. Also the first experiments with the control algorithms are done with the ATV platform. In the last phase, if the system works well enough, it will be moved to a commercial full-scale forest harvester for final testing.

This paper consists of the following sections. First, the used methods and tools are discussed. Then the results including real-time SLAM with scan correlation, and feature based data association and global mapping are presented. Finally some conclusions about the applicability of the tested approach are given.

II. Methods and Tools

A. ATV Platform

The ATV platform is shown in Fig. 1. 2D and 3D laser range finders, machine vision camera, differential GPS receiver and MEMS inertial measurement unit are connected to a computer to form the data collection system.

The 2D laser range finger is used continuously while the 3D laser range finder is used only for reference measurements while the platform is stationary. The 3D scanner is unsuitable for continuous measurements because it takes several minutes to make a 3D scan. The machine vision camera is synchronized to the 2D scanner. A custom hardware divider is used to transform the synchronization signal from the laser so that it can be used to trigger the camera which operates at a much lower frequency.

The differential GPS is the same model that is commonly used in forest harvesters. It has much better gain than most consumer level receivers so that it can maintain better satellite fix even in demanding forest environments. MEMS inertial measurement unit is used to provide information of the pose of the platform.

The box in the front acts as a stand for the different sensors while the box in the back contains a 24 V battery for system power. The ATV has a 24 V generator which charges the battery when the engine is running. An inverter is used to provide 250 VAC. Both laser range finders operate directly from the battery while other instruments use ordinary switched-mode power supplies to provide 5 V and 12 V operating voltages.

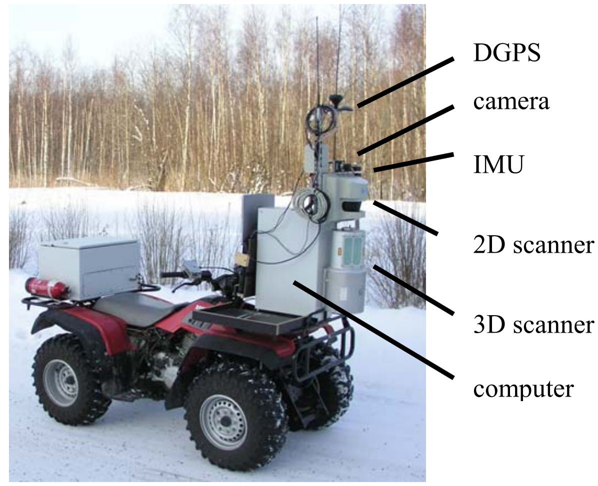

Fig. 1 The Forestrix Project ATV Platform

B. Positioning with scan correlation

Unprocessed scan correlation is the process of aligning an observed set of points with a reference point set. Scan correlation may be defined as a function of the relative pose between the two data sets. The two point sets in this paper are two laser scans named the reference scan and the observation scan, where the fixed reference scan defines the base coordinate frame. Correlation involves finding the pose of the observation scan relative to this base coordinate frame. Scan correlation is used here to do short term sensor-based dead reckoning, which is an alternative to odometry in rough terrains like forests.

There are numerous different scan correlation (set of points correlation) methods available to be used for sensor-based (laser-based) dead reckoning. In this chapter two methods are briefly introduced. The methods are Iterative Closest Point (ICP) and Sum of Gaussian (SoG). Different scan correlation methods are presented e.g. by Bailey [16].

C. Scan correlation methods

1) Iterative Closest Point

The Iterative Closest Point method is probably the most commonly used and widely known range-image registration technique. It is a non-probabilistic technique which popularity derives mainly from its simplicity and efficiency. The algorithm is initialized with an initial pose estimate and, until the estimated pose satisfies some convergence criterion, it is iteratively refined by a process of point-to-point data association and least-squares transformation. Convergence of the algorithm occurs when the nearest neighbor for each point does not change between iterations. However, it might also be determined by a least-mean squared residual threshold, or simply a fixed number of iterations.

There are three basic shortcomings to the ICP algorithm.

First, it performs explicit point-to-point data association each iteration cycle, which introduces error since the points in each scan represent a surface and not a set of discrete locations. Second, ICP converges to local minima and so requires a good initial pose guess to find the global minimum. And third, the ICP result is a least-mean squares estimate where each association pair is equally weighted; there is no direct means to incorporate modeled sensor uncertainty or to obtain an estimate of pose uncertainty in the solution [8], [16].

2) Sum of Gaussian

The Sum of Gaussian method is a probabilistic technique which yields superior results compared to the ICP method discussed above. Principally, the SoG method is the conversion of scans of range-bearing measurements swept in a 2-D plane to a Gaussian sum probability density function (PDF) and equations for the calculation of the cross-correlation of two such PDFs to get the pose change between scans. In Fig. 2 Cartesian Gaussian sum probability densities are calculated for one measurement scan. This scan is from forest environment with 180° bearing and PDF calculation was restricted to range of 15 meters [8], [16].

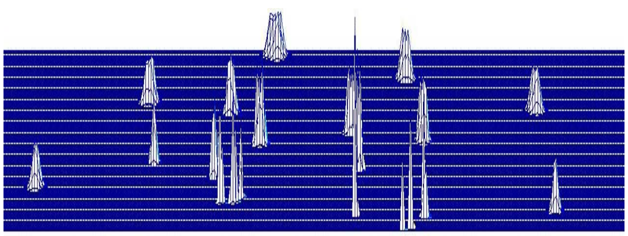

Fig. 2 Probability densities of Cartesian Gaussian sum [8]

D. Feature Based SLAM

The overall structure of the feature based SLAM algorithm is shown in Fig. 3. The SLAM is based on the raw 2D laser range finder data. The first step is the feature extraction. In this application, the features are the surrounding trees. The tree features identified from a single scan are called echoes due to their uncertain nature.

In a clean forest with little or no underbrush it is relatively simple task to find the tree trunks from the raw laser scans. This is done in the second step. However, in more dense forests finding the trunks can be extremely difficult if not impossible. The dense vegetation also reduces the effective measurement range drastically. Even in relatively clean forests the blind areas behind the nearest trunks can be substantial.

While it is straightforward to extract the echoes from the raw scans, it is very difficult to identify individual trees. This problem of matching features is usually referred as the association problem in the SLAM literature. Many SLAM applications get around of this problem by using beacons that can be unambiguously identified. However, this approach is not feasible in the proposed forest mapping application. A single tree trunk is difficult to identify because they all look the same for the laser range finder. Even the variation of trunk diameter can be very small in a well managed forest.

Instead of trying to identify individual trees it is better to identify groups of trees. The tree groups are identified in the third step. The tree groups offer a variety of features that can be used for identification: distances and angles between adjacent trees and trunk diameters. One of the central challenges in this approach is that tree groups are not constant. Depending on current position, not all trees may be visible because of the blind areas.

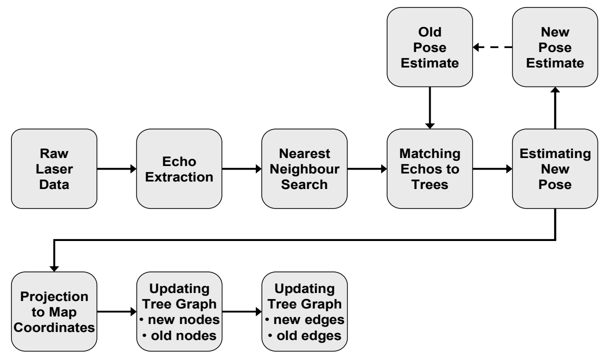

Fig. 3 Information flow in feature based SLAM

The matching of echoes to the tree map is done in the fourth step. The matching is done a group at a time. The tree map is stored as a graph structure which makes this a graph matching problem. However, there are some issues that will have to be taken into account. First, the echo graphs are usually incomplete because of the blind areas. Second, the tree graph is usually not complete, because it is incrementally built. The matching algorithm uses distances between adjacent tree trunks to match tree groups. Distances between trees are easy to work with because they are translation and rotation invariant. Relative angles are more difficult to work with because they need an additional reference point. If three trees are matched together in a triangular configuration, as shown in Fig. 4, the distance information alone describes the full geometry making the relative angles completely redundant. For this reason, the relative angles are not used for matching tree groups. Absolute angles (e.g. relative to magnetic North) could be

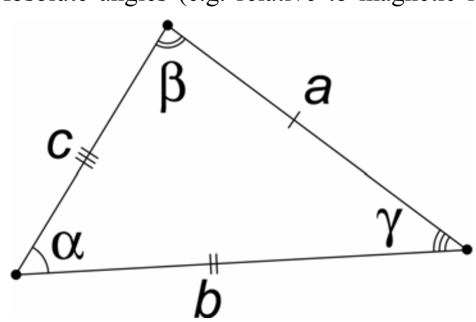

Fig. 4 Distances and relative angles contain the same information

useful for matching purposes, but the current measurement platform does not have a reliable and accurate instrument for measuring absolute angles.

fter the echoes have been matched to the trees, a simple algorithm is used to estimate the new pose. First, the “centers of gravities” of both set of points are calculated and the echo set is then translated so that the CoGs coincide. Second, the average angle between all echo-tree pairs is calculated and the echo set is then rotated by this angle. Care should be taken that all the angles are calculated on the correct cycle. This algorithm is based on the realistic assumption that the subsequent scans differ only by a translation and a rotation.

In the final phases the echoes are projected to map coordinates. At this point they are classified either as new or old trees. New trees are added to the tree graph and diameter information for the old trees is updated. The closer the scan is taken, the better the diameter information usually is. New edges are also inserted into the tree graph and old edges are updated to reflect the new information. Only the distances between the trees are recorded.

One of the problems of the presented algorithm is that it makes the optimistic assumption that all echoes really are trees. This helps the algorithm to acquire new trees and to keep going, but if echoes of branches are falsely interpreted as trees they will be added permanently to the tree map. To solve this problem another algorithm was added to remove false positives from the tree map. This algorithm is shown in Fig. 5

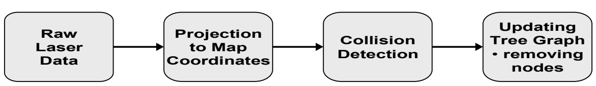

Fig. 5 Removal of false trees in feature based SLAM

The algorithm works by projecting laser scans to map coordinates and then using a collision detection algorithm to find intersections between the “rays” and the trees in the map. If there are more “rays” passing through a tree than there are valid measurements of that tree, the tree is removed from the map. This second algorithm was added as an afterthought and it reflects the inability of the first algorithm to record what is sometimes referred as negative information. Future improvements of the algorithm may use local occupancy grids to keep track of areas that are known to be free of trees.

The tree graph is a hybrid data structure. The graph structure contains the nodes and the edges between them. Each edge has length and in future versions also direction. However, each node has also position in a Cartesian coordinate system. The possible mismatch between Cartesian positions and edge lengths can be used by a third algorithm to distribute the accumulated error evenly e.g. when a large loop is being closed. Currently this is done with a simple iterative algorithm that tries to minimize and distribute the tensions in the tree graph.

E. Improved data association

Data association is one of the most critical issues for SLAM implementations. Some new measurements must be associated with existing map features during SLAM procedure. Most common way to make data associations is to use statistical validation gating [17].

Important advance is the concept of using multiple associations simultaneously by exploiting geometric relationship between landmarks. This is called batch gating which has two existing forms. First is the joint compatibility branch and bound (JCBB) method [6]. It is a tree-search method and similar adapted version is used in the Forest SLAM method. Second method is the combined constraint data association (CCDA) [16], which is a graph search.

Data association algorithm used in Forest SLAM is based on batch gating. Only edges between nodes in graph are used to calculate compatibility. This is the only used geometric relationship between landmarks in the tree map and echo map graphs. Diameters of trees have also been tested to validate compatibility, but no added robustness was achieved. No pose information is needed but it can be used to narrow the search space. This association method is only used if more simple statistical validation fails. Failure is noticed if new pose differs too much from previous pose.

Algorithm 2.1: CalculateBestSubGraphFit(E, N)

L = Ø
for each echo $e \in E$ **do**
minError = LIMIT
W = Ø
for each node $n \in N$ **do**
// M is a list of common nearest
// neighbors ($m_e \rightarrow m_n$)
(M, error) = calcError(e, n);
for each nearest neighbor $m \in M$ **do**
//calculate combined error
(M, err) = calcError(m_e, m_n)
error += err
end for
if (error < minError)
minError = error
W = ((e $\rightarrow$ n), M) // set best match
end if
end for
L $\leftarrow$ W // update best fit
end for
return L

Main idea of the method is to find best match of node and its two or more neighbors according to goodness of fit calculated from matching edges in the echo graph and the tree graph. The batch validation done is shown in Algorithm 2.1. Nodes N can be all the nodes in the graph map or just a portion. So it can be used as a global data association method or a more local one. As shown in Fig. 6 goodness of fit is calculated from edges combining chosen node and its closest neighbors. Only the best matched sub graphs are used in localization and tree mapping steps.

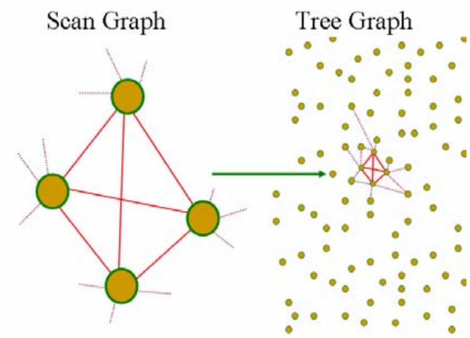

Fig. 6 Scan graph and Tree Graph batch validation by using tree-search algorithm

The goodness of fit is calculated as a chi-square statistic sum of differences between distances (d) to neighboring nodes from observed (E, echoes from scan) and expected (N, nodes from graph map) outcome, each squared and divided by the expectation, equation 1.

$$\chi^2 = \sum \frac{(d_E - d_N)^2}{d_N} \tag{1}$$

III. RESULTS

A. Combined SLAM

Sum of Gaussian method is used to give the first estimate to feature based SLAM part of the algorithm. SoG-algorithm is implemented with C++. While the current version of the SLAM software is written in Java programming language there was no need to change SoG implementation because C++-code can be called from Java [8].

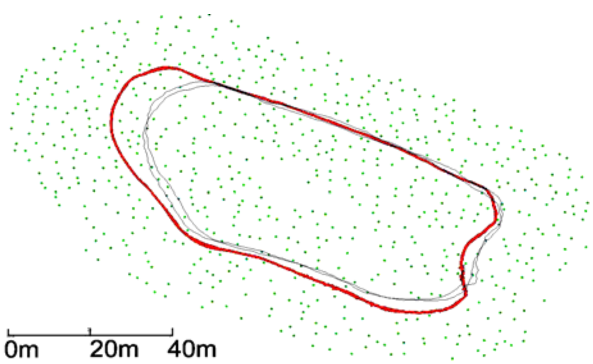

Fig. 7 Tree map produced by Forestrix SLAM

Feature based SLAM uses laser-based odometry as a first pose estimation and then iterates the true pose according to the extracted and matched features (the dotted arrow in Fig. 3). Laser-based odometry is only used to calculate movement between two laser measurements. Cumulative errors using solely odometry information grows too large in short time.

In Fig. 7 there is a tree map produced by Forestrix SLAM. The DGPS path is marked with a narrow line and the SLAM path is drawn with a bold line. The measured tree positions are also shown. The same loop was driven twice. These positions and diameters have been compared to hand measured tree information provided by METLA (Finnish Forest Research Institute). At this time combined Forestrix SLAM works in well defined forests.

B. Software

The current version of the software is written in the Java programming language. Different parts of the user interface are shown in Fig 8. and in Fig 9.

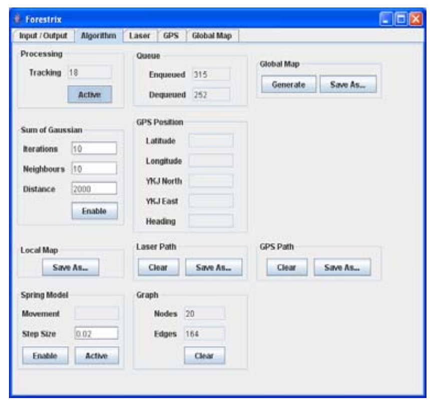

Fig 8. The GUI provides means to specify inputs and outputs and to select algorithms.

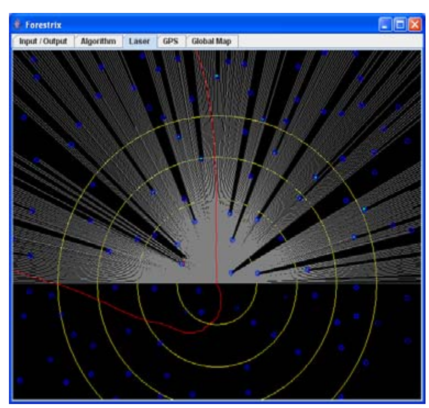

Fig 9. The operator can see a visualization of the most recent laser scan, the forming of the tree map and the traversed path. In the figure the ATV has returned to the starting position

The software can read input data either from data files or from actual sensors. The data files are essential for testing the system in laboratory environment. The software can connect to the 2D laser range finder and the DGPS receiver. The SLAM path can be matched to the DGPS path. As a result the algorithm also gives the tree positions in absolute map coordinates. The resulting absolute accuracy is mostly limited by the DGPS receiver. The DGPS receiver has too much localization error to make this only a mapping problem. So SLAM has to be performed and GPS data is used to calculate an estimate of the global tree positions. Global measurements can also be used to minimize the data association search done to the tree graph.

Measurement of mapping accuracy of generated maps has been one of the problems in this project. Comparisons have been done against manually measured map which is not accurate enough for the position information of the trees. It has been mainly used for tree diameter information error calculations. Results depend on the scanner resolution used. With high resolution diameter error is small up to 15 meters, but with lower resolution diameter error grows even faster as the distance to measured tree grows.

Comparison against a map generated from 3D laser scanner measurements is under construction. 3D Map generation is done using methods presented by Forsman [11]. This would be used as a ground truth.

Measurement of localization accuracy of the generated harvester path is also a problem. Localization works fine in small areas. Comparison against GPS path is not feasible because it is far too inaccurate. Comparison against RTK-GPS path was considered but it turned out that the RTK-GPS used did not get a reliable fix when moving in a forest environment. Accumulated position error can also be estimated by measuring the jump the algorithm makes when closing a loop. Problem is that there may be a series of small jumps when previously measured tree groups are identified.

IV. Conclusions

The current algorithms implemented in the Java programming language run somewhat slower in modern laptop computers than what is required for real-time applications. Some parts of the presented SLAM algorithm can be easily tuned for better performance. Java is a safe language which makes it easy to program with but it is not the best programming language performance-wise. Also interfacing it with exotic hardware such as 2D laser range finders can be difficult. C++ implementation may have to be considered in later phases of the project.

A forest environment is very tough for precision instruments. Luckily there are models of 2D laser range finders and DGPS receivers that are designed for outdoor environments. The forest terrain is in many cases quite rough, which adds additional challenge for the sensor system. It may be necessary to tilt the sensor package when the harvester is working in an inclined position while traversing steep slopes.

More development work is needed to find better solutions to the association problem. The current system works well for small loops. However, the accumulation of errors may be a problem for larger loops. Identifying trees may also be a problem in more dense and cluttered forest environments.

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