Navigation of Mobile Robots in Natural Environments: Using Sensor Fusion in Forestry

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ABSTRACT

Navigation using GPS is a common strategy which cannot provide the desired accuracy in forests. In the forestry of North Rhine-Westphalia (Germany) algorithms are developed to delineate single trees from remote sensing data. These generated tree maps can be used to create a virtual testbed. Different kinds of sensor data can be merged to form a "visual GPS" system which improves accuracy for the navigation of autonomous vehicles in the forest. Algorithms were developed, which provide localization results accurate enough to allow navigation to a single tree.

Keywords: navigation, forest, sensor fusion, mobile robots, GPS, particle filter

1. FOREST NAVIGATION

Navigation is not only needed on streets or in space exploration missions but also in forests. Modern machines like wood harvesters can automatically cut trees, remove branches and cut the stems into pieces but an expert is still needed to plan a thinning and to mark the trees to be felled. This process can be sped up if the forest ranger can mark the trees to be cut virtually using geographic coordinates instead of colored crosses sprayed on the stems. Marking the trees can be omitted in the favor of augmented reality and they could be displayed on a head-up display but the wood harvester has to be able to locate itself accurately to allow automatic navigation to the next tree for cutting.

Using GPS for navigation is a widely spread strategy which yields sufficient accuracy in most applications. However, signal absorption in the canopy leads to poor results in a forest with errors up to 50m and more. Furthermore, the canopy causes intermissions and signal loss for several seconds. The performance can be even worse on a moving vehicle where the signal can get lost until the vehicle reaches an open area or stops. Beyond that, simple assumptions, such as a vehicle only moving along a road with a certain distance to the next parallel road, do not hold in a forest. Forest roads are seldom mapped precisely and autonomous vehicles in a forest might need to leave them.

Another problem is that even if a detailed terrain model is available other factors as understory and ground humidity might influence the movements of an autonomous robot in the forest. Wheel spin and slipping can induce errors in a position calculated based on forward projection and odometry.

Other approaches as described in [6] and [7] use differential GPS (DGPS) sensors as their main source of information on the position. In [7] a DGPS sensor is combined with laser scanners and a Kalman Filter approach. However, our experiments with a high precision DGPS sensor showed that the accuracy is not nearly satisfactory for navigating to a single tree and logging the precise location of every tree that is felled by a wood harvester along with other attributes as the diameter and its volume. Especially high-precision DGPS sensors suffer from signal loss under the canopy as they demand a number of strong signals to calculate a reliable position. If there are not enough satellites available the position is not updated at all.

Currently, techniques are being developed to delineate single trees from remote sensing data. [3] presents a method to semi-automatically delineate single trees from airborne laser scanner data. Along with the trees and their geo-coordinates the height and the diameter at breast-height are determinated. This data can be used to generate a tree map, which can be used for navigation. This map has a mean error between 0.5 and 1.5m which is still below the mean tree distance of about 2.5m.

2. LOCALIZATION

In order to test the algorithms described below, a virtual model was created based on the calculated tree map. It contained the forest as well as a wood harvester, which was operated as an autonomous robot. Furthermore, the harvester was equipped with virtual laser scanners to retrieve the required information about the surrounding.

The first tests were conducted in a virtual environment. In order to take the evaluation of the algorithm a step further a data logging part was added to the algorithm. It allows recording sensor data on a real machine and provide it for playback.

Laser Scanner

To simulate laser scanners in the virtual environment, an interface was created which allowed the connection of a real laser scanner via TCP/IP as well as to simulate laser scanners. The virtual model can change during simulation. Therefore, no static model can be used for the calculation of the simulated distance measurement. As the scene has to be rendered for display on screen and to guarantee fast calculation, the calculation is performed on the graphics card.

To simulate a laser scanner a field of view of 180° has to be covered. At an angular resolution of 0.01° the number of pixels which are needed in the horizontal line amounts to 18,000. As the size of the internal buffer is limited multiple depth-images are rendered off-screen and the depth information is extracted.

On that basis, a comparison between simulated data and real data was possible. It showed that the occurring errors consisted of three kinds of measurement errors: those errors that can be modeled as Gaussian errors, measurement errors due to strong curvature or objects oriented almost parallel to the laser beams and errors as a result of materials with poor reflection characteristics. Errors due to reflectance cause maximum or minimum values of the scanner range or values denoting invalid measurements, depending on the specification of the laser scanner. They can be filtered easily and were of no further concern. Errors due to curvature or object orientation were simulated by calculating the gradient Δ of the object surface at the point where a single laser beam hits the object. With r_1 and r_2 denoting two consecutive range measurements and α describing the angular resolution of the laser scanner the gradient can be calculated as:

$$\Delta = \frac{r_2 - r_1}{r_1 \tan(\alpha)} \qquad (1)$$

The measured range values are distributed based on an one-sided Gaussian distribution where the standard deviation σ corresponds to the gradient Δ and the mean value μ corresponds to the measured range value r_2. This leads to the probability distribution for the noisy distance measurement r:

$$p(r|_{r<r_2}) = 0 \quad p(r|_{r \geq r_2}) = \frac{\sqrt{2}}{\sigma\sqrt{\pi}} \exp\left(-\frac{1}{2}\left(\frac{r-\mu}{\sigma}\right)^2\right) \qquad (2)$$

Apart from the horizontal gradient the vertical gradient has the same impact on laser scanner accuracy. The gradient has to be calculated twice, once for each direction, and the probability distributions for each direction are multiplied.

In forests, the largest differences in the range measurements occur along the horizontal direction, for example at the edges of trees. Therefore, changes perpendicular to the plane of the laser beams were neglected as trees were the only objects of interest in this context and it allowed much faster calculation without loss of crucial information.

In the simulated or real laser scanner data, trees can be identified as described in [9] and shown in figure 1. The approach convolutes circular masks with the laser range measurements and applies filters to detect areas where the laser beams hit the ground to avoid misunderstandings of the surrounding. The found trees cannot be directly used as landmarks for autonomous navigation.

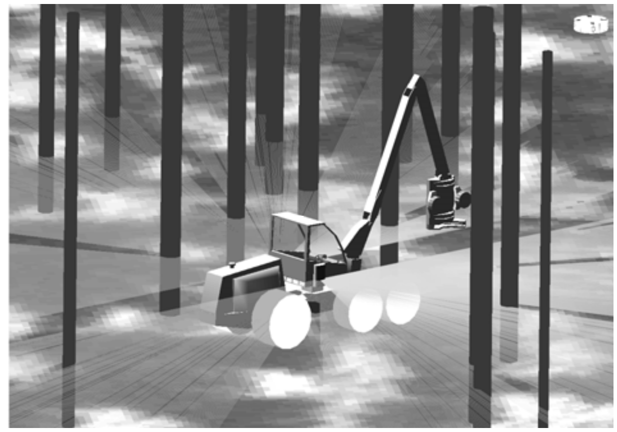

Figure 1: Laser scanner beams and identified tree group

"Visual GPS"

The idea of the Visual GPS is to bring current developments in the field of robotics into the forest and combine them with information on forest inventory such that the result outperforms other navigation approaches. A matching algorithm is run based on a tree map, which was generated from remote sensing data, and the tree group, which was detected by one or more laser scanners.

Therefore, a particle filter algorithm as described in [4] was implemented as it allows considering different kinds of distributions. Particles are also called random state samples and each particle is a hypothesis as to what the true world state might be.

In the initialization, particles are distributed uniformly. An importance weight w_t is calculated for each particle incorporating the measurements, as described below, and a sampling step is performed, rejecting particles with a low importance weight and replacing them with new particles, which are distributed according to the posterior. This process is repeated until the particle distribution concentrates at one point and the particle with the highest weight is returned as the result.
A single tree as a landmark cannot be associated with its corresponding tree in the map. However patterns of tree positions can be matched.

The position of an inaccurate GPS sensor is used as an initial guess and the particles are distributed in an area with the GPS position at its center. As shown in figure 2, a square area was chosen to guarantee even particle distribution and short calculation time. Each particle represents a hypothesis for the position of the vehicle and is tested for its probability to represent that position.

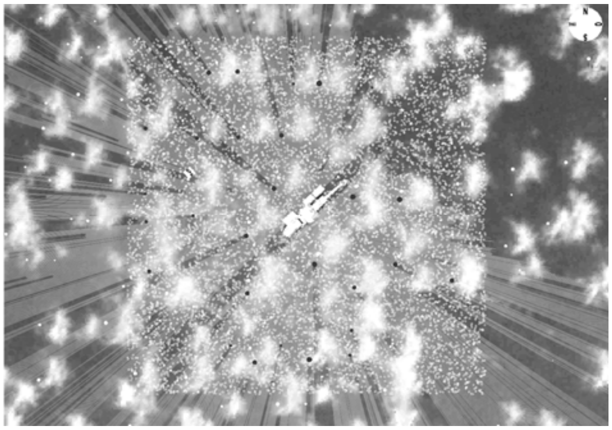

Figure 2: Particle initialization

Rotation Invariant Approach: As not only the location of a vehicle in the forest is unknown but also its orientation a rotation invariant approach was chosen.

The particles were initialized according to a random uniform distribution $\overline{bel}(\mathbf{x}_0)$ centered at the probably faulty GPS position. The size of that area will be discussed below. For each particle $\mathbf{x}_t$ a number of candidate trees are extracted from the tree map. Candidate trees are trees in the tree map which could correspond to trees in the tree group found by the laser scanners. That means that their distance to the position represented by the particle $\mathbf{x}_t$ is not larger than the maximum distance of the trees in the tree group to the reference point $\mathbf{x}_R$, which represents the seeked position in the laser scanner frame. As a probability measure for the current particle the minimum difference of the distances of the candidate trees to the particle position and the trees in the tree group to the reference point is calculated. Therefore the importance weight w_t is proportional to the described difference.

$$w_t^{[m]} \propto \sum_{tree\,group} \min_{candidates} \left\| \mathbf{x}_{tree} - \mathbf{x}_R \right| - \left| \mathbf{x}_{candidate} - \mathbf{x}_t \right\| \quad (3)$$

The propagation step is performed according to the sum of minimal distances for each particle. For the resampling step a normal distribution is used. With an prediction of the particles described by $\overline{bel}(\mathbf{x}_t)$ the posterior $bel(\mathbf{x}_t)$ after the resampling step can be described by

$$bel(\mathbf{x}_t) = \eta p(\mathbf{z}_t \mid \mathbf{x}_t^{[m]}) \overline{bel}(\mathbf{x}_t) \quad (4)$$

where $\mathbf{z}_t$ is the measurement (the tree group) and η is a normalization constant. An example of the particle distribution after one resampling step is shown in figure 3.

The rotation invariant algorithm does not directly provide information on the heading of the vehicle which is important for calculating the position of the harvester aggregate and thereby detecting the position of a tree which is felled. To determine the orientation each tree in the tree group is appointed its counterpart by detecting the tree with the same distance from the calculated position as the distance of the tree to the reference point. From the positions of the trees the rotation of the reference frame to the tree map frame can be calculated. In the generated list outliers are filtered and the heading is calculated as the mean value of the angles of the remaining particles.

This approach worked well in the case of an ideal tree map. As described above, the mean error in generated tree maps lies between 0.5 and 1.5m and the rotation invariant approach sufferst from that mean error.

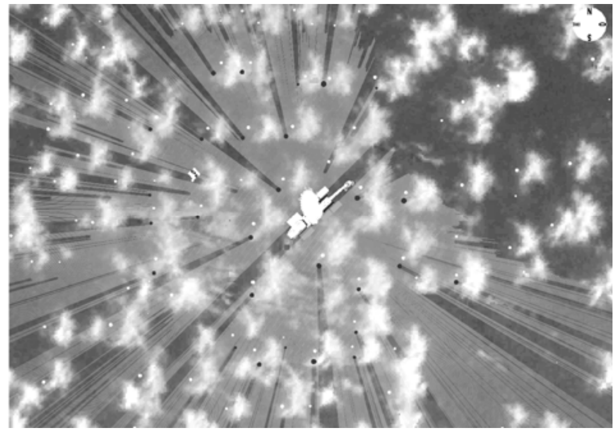

Figure 3: Particle concentration after resampling

Rotation Variant Approach: In order to make the approach more robust against faulty tree maps the rotation invariant approach was rejected and a rotation variant approach was implemented determining the heading of the vehicle along with its position. Therefore, the probability measure used in the propagation step was enhanced. Instead of embracing only the distances of the trees to the reference point, their relative position is used considering the heading φ_t of the current particle:

$$\begin{aligned} & w_t^{[m]} \propto \sum_{tree\,group} \min_{tree\,candidates} \left| \begin{aligned} &\left|(x_{tree,rot} - x_R)\right| - \left|(x_{candidate} - x_t)\right| + \\ &\left|(y_{tree,rot} - y_R)\right| - \left|(y_{candidate} - y_t)\right| \end{aligned} \right| \\ & with \quad x_{tree,rot} = x_{tree} \cdot \cos(\varphi_t) + y_{tree} \cdot \sin(\varphi_t) \\ & and \quad y_{tree,rot} = -x_{tree} \cdot \sin(\varphi_t) + y_{tree} \cdot \cos(\varphi_t) \end{aligned} \quad (5)$$

The rotation variant approach directly calculates the heading of the vehicle but the sensibility towards rotation, which results from the new probability measure, leads to a higher number of particles which have to be used during the initialization step.

Global Search: Experiments on a test area with about 22,700 trees proved that the algorithm worked reliable for tree groups containing 20 or more trees and for position errors of the magnitude of the mean tree distance. Similar tree groups could not be found within the forest. However the calculation time was too long as to be used for navigation.

Local Search: To overcome the high calculation time the number of particles had to be reduced. Therefore the initial position is estimated by using an ordinary GPS sensor. Although the GPS measurement is faulty in the forest it can limit the search to a restricted area. Machines most often start at the edge of a forest stand, at a forest road or a canopy opening. At these spots the canopy usually is transparent and GPS sensors work with higher precision. Therefore, they provide a good initialization for the algorithm.

In the following steps the previous position can be used instead of the output of the GPS sensor for determining the search area. The previous position provides a better initial pose estimation than the GPS sensor and therefore gives the opportunity to further decrease the search area.

To reduce the number of trees for which the distance has to be calculated, trees with a distance from the initial pose estimation $\mathbf{x}_{GPS}$ smaller than the sum of the estimation of the maximal position error and the maximal distance of the trees in the scanned tree group from the reference position are extracted from the tree map:

$$\left|\mathbf{x}_{candidate} - \mathbf{x}_{GPS}\right| < r_{error} + \max_{tree\,group}\left|\mathbf{x}_{tree} - \mathbf{x}_{R}\right| \qquad (6)$$

Another way to reduce the search area is to estimate the orientation of the vehicle. Estimation of the orientation is difficult for machines such as wood harvester. It moves very slow and stops frequently when cutting trees. Therefore small lateral position differences result in large orientation deviances as the difference vector does not directly point into the direction of the movement any more. Another approach is to use sensor fusion and mount a compass onto the vehicle. During particle initialization the angle can be restricted to the domain of uncertainty around the compass orientation. However, mounting a compass onto a wood harvester proved to be a serious problem as the harvester machine has a massive metal body and as such disturbs the compass measurement.

3. RESULTS

The simple criterion presented here proved to be reliable in the vast majority of cases. Problems can occur when the tree group contains trees that are not part of the tree map (“false positive”). This can happen due to missing trees in the tree map or faulty tree cognition in the local laser scanner measurement. In the first case, the understorey might not have been detected in the airborne laser scanner data. In the second case, other objects like the harvester’s aggregate might have been mistaken to be a tree or the laser beams might have hit the ground and a tree is detected in the irregular measurement due to the structure of the ground.

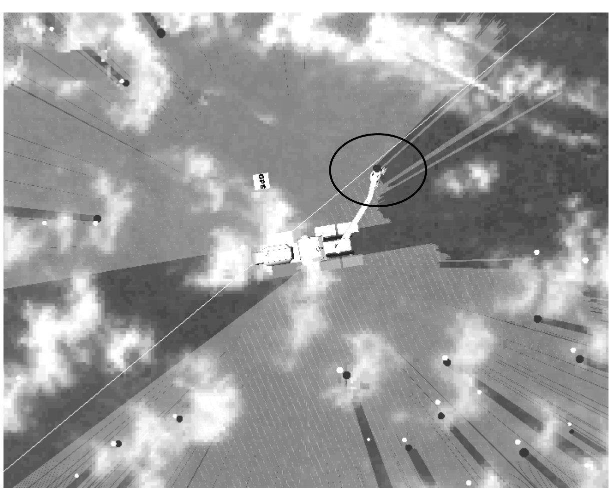

Figure 4: An example of a false-positive tree at the position of the aggregate.

The case of trees not detected in the local laser scanner measurements but contained in the tree map (“false negative”) does not lead to problems in the pose estimation step. The reason for this is that the algorithm searches for a corresponding tree for each unit in the tree group. For a false positive no corresponding tree can be found whereas a false negative is simply not considered. However, if the size of the tree group is too small the estimation errors grow. The minimum number of trees depends on the search area radius. A size of 20 trees proved to generate reliable pose estimations even during the global search. Dropping below 15 trees the number of faulty position increases rapidly as more similar patterns can be found.

Single faulty positions can be filtered in respect to the movement constraints of a harvester. The velocity is very low and the orientation cannot jump. In the experiments cycle times of about 0.5sec were reached on a standard PC. As forest machines do not demand very short calculation time, the algorithm proved to run fast enough to allow identification of single felled trees on board real machines. There, one application of the algorithm was to support a navigation assistant to the next tree similar to navigation systems in cars.

To evaluate the accuracy of the system on a real wood harvester a surveyor’s office was instructed to measure the vehicle’s position at 7 distinct locations. At each position the sensor input data was written to file for several seconds. This data was evaluated and for each location more than 45 pose estimations were calculated. The mean error amounts to approximately 0.55m.

4. FUTURE WORK

The algorithm can be further tuned for better performance, especially run-time, by reducing the amount of particles needed based on better estimations of the position and the orientation. Furthermore a new algorithm for the detection of trees in the laser scanner data is being developed based on the assumption that vertical structures with a size in the range of the diameter of a tree are rare in forests and trees do not necessarily have a circular cross-section and therefore matching circular rings can be omitted.

The reliability can be enhanced by using a detailed digital ground model and the cabin tilt in order to detect the area where the laser beams hit the ground and therefore avoid the detection of false positives. Similarly the position of the aggregate, which can be measured by integrating sensors in the hydraulic cylinders of the crane, can be cut from the laser scanner measurements and be ignored during tree detection further reducing the amount of false positives in the tree group. With the integration of an outlier rejection step for false positives in the detected tree groups that ignores trees for which no corresponding candidate tree can be found, a more accurate importance factor can be calculated.

Another task is the integration of the algorithm with a Kalman filter [4] to allow real-time performance of the algorithm. Therefore, the Kalman filter is initialized with the pose estimation of the particle filter algorithm, which is also used for continuous checks of the current position estimate thereby combining two algorithms with different advantages. The Kalman filter allows real-time execution and therefore speeds up the overall navigation algorithm. The particle filter algorithm can periodically check the position estimated by the Kalman filter and correct it. Furthermore it presents a strong method to cope with two main problems in mobile robotics: the data association problem and the kidnapped robot problem.

Simultaneously, a mapping and map correction algorithm could be integrated into the system so that understory trees, which cannot be detected using remote sensing data, and deciduous trees, and therefore are more difficult to delineate in airborne laser scanner data, can be added to the tree map.

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