LOCALIZATION IN LARGE-SCALE UNDERGROUND ENVIRONMENTS WITH RFID

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ABSTRACT

Localization using satellite-based GPS is not available in underground mines, therefore a new approach is required. This paper presents a method for localizing a sensor-equipped vehicle in a large-scale underground environment by using a particle filter and a collection of 2D a priori *node maps*. Sporadically placed passive RFID tags are used in the creation of the locally consistent node maps and for helping to solve the global localization problem. Experimental results from real-time localization in the multi-kilometre Carleton University underground tunnels are presented.

Index Terms— Robot localization, RFID, filtering

1. INTRODUCTION

The satellite-based Global Positioning System (GPS) is widely employed in surface mining to improve productivity, safety, and streamline operations. GPS, however, cannot be used in underground environments like tunnels and mine drifts. Furthermore, using time-of-flight radio for localization is problematic in underground environments due to multi-path issues, poor accuracy, and logistics. An inexpensive underground positioning system that allows mining companies to monitor vehicles and enables vehicle operators to accurately know the position of all vehicles would be significant.

The localization system presented in this paper was not designed for exploring unknown environments or performing on-line simultaneous localization and mapping (SLAM). The work presented here was specifically designed to localize underground mining vehicles in real-time within an *a priori* map, similar to a car driver using GPS to localize above ground within a known highway map. For the system described here, no infrastructure is required in the mine except for sporadically-placed passive RFID tags. Several goals were set for the system, including the ability to handle large-scale environments (e.g., tens of km), a necessity for minimal human input, low computational burden, and sufficient accuracy for vehicle tracking purposes (e.g., ± 5 m, ± 5 degrees).

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1.1. Localization with RFID

Works such as [1, 2] use dense arrays of RFID tags and their Radio Signal Strength Indicator (RSSI) in order to perform localization. The patterns, spacing, and large number of RFID tags used in a small area make those approaches impractical in a large scale mining environment. In this paper, RFID tags are used only sporadically (spacing of 50 to 300 m) and the only requirement is that the RFID tags remain static. Furthermore, the RFID tags are installed without any measurements and it is not necessary to know their global positions.

This paper builds on the work found in [3] where the goal was to produce globally-consistent metric maps of unstructured and very large-scale environments using RFID tags. That work used the method from [4] for enforcing consistency of the map by recognizing similar scans taken by range measurement devices and by performing a global optimization over a "closed-loop" set of pose estimates.

Here, a particle filter is used for localization, which is based on recursive Bayesian filtering and is commonly used in mobile robotics [5]. The method consists of using particles to represent the posterior probability. Each individual particle represents one possible vehicle pose. For this implementation the environment is assumed to be flat (2D) and changes in elevation are not measured or accounted for.

As shown in [6], particle filters can be very robust, can globally localize a vehicle and can recover from a "kidnapped" robot situation even though they are not as fast or accurate as other methods such as Kalman filters. In this paper, our implementation of the particle filter largely follows the current literature with the exception of the introduction of RFID tags for global localization and the use of occupancy grid maps incorporating RFID tags that we call *node maps*.

2. SYSTEM DESCRIPTION

This section briefly describes the algorithms underlying the developed localization system. Briefly put, the system works by: 1) collecting data about the environment for mapping purposes; 2) generating a set of occupancy grid maps; and, 3) employing a particle filter-based algorithm to localize the ve-

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hicle, in real time, within the generated maps. This paper focuses on the evaluation of Step 3: underground localization.

2.1. RFID Tags and Map Creation

The only constraint on the placement of RFID tags is a convention that RFID tags be installed in longer tunnels, not in intersections. The reason for this should become clear later. Step 1 of the process is to collect data for mapping by driving a sensor-equipped vehicle (see Sec. 3) through the underground environment. The RFID tags are then employed as unique markers to segment the data into pieces that start and end with detected RFID tags. Preliminary work on the mapping process was covered in a previous work [3].

A few methods for mapping large-scale environments exist but they to do not easily lend themselves to localization. For example, Bosse et al. [7] presented a method using an 'atlas' framework. However, the maps produced are not locally consistent (1:1 mapping with the environment) and they are not of sufficient resolution for our application. Another problem is that a moving vehicle can reside in many misaligned sub maps at any instance in time, which is computationally expensive and could lead to divergence of the vehicle location. Finally, very large-scale environments, like those in mining, present computational challenges for global localization.

This paper uses 2D occupancy grid maps referred to as *node maps* (see Fig. 1). Each RFID tag has an associated node map. An RFID node map consists of all tunnels that connect it to every other directly reachable RFID. If a vehicle is initially at an unknown location, detecting an RFID places the vehicle on that tag's associated node map and within the detection range of the tag. A particle filter is then initialized and the vehicle location is tracked in the current node map.

A node map has the following key properties: 1) it is locally consistent and has as a high resolution (cm); 2) it contains every directly reachable RFID; and, 3) it has an overlapping area with each adjacent node map. The particle filter tracks the position of the vehicle on a single node map and then switches to the next one in a discrete step.

An RFID-based node map is built by grouping together all data segments that contain *every* directly reachable RFID, aligning them at the main RFID and "closing the loop" on the poses [3]. The overlapping area between any two node maps need not exactly match in size or orientation; see Fig. 2C. Since individual node maps do not contain large tunnel loops, they may also contain global errors. However, position tracking works at the local level. Inconsistencies in the environment can cause the localization algorithm to diverge. Thus, for node maps it is important to ensure they are 'small' enough to maintain local consistency.

2.2. Jump Locations

Since the global environment is represented by smaller node maps, it is necessary to quickly track the pose of a vehicle

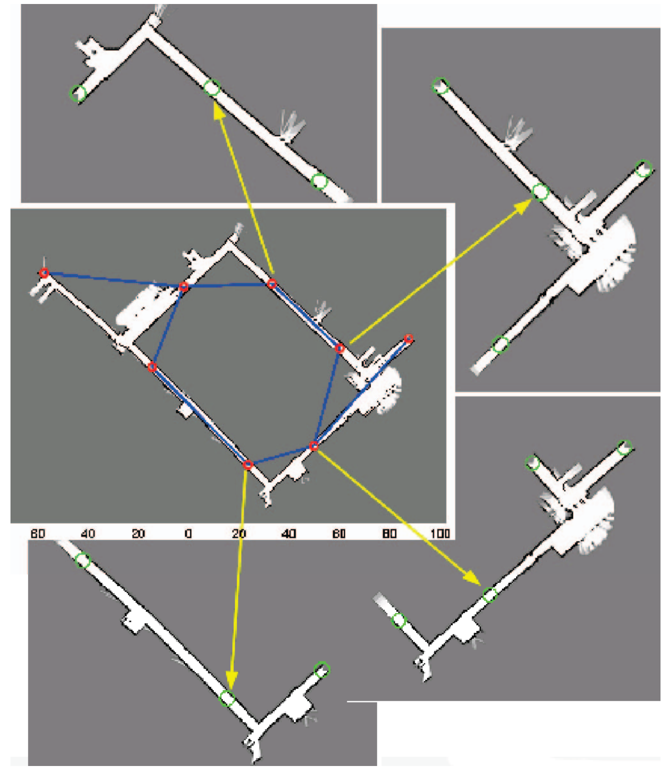

Fig. 1. A 'global' map (center) and node maps for RFID tags.

over many node maps as the vehicle traverses the environment. The discrete step of moving the estimated pose of a vehicle from one node map to another is referred to as *jumping*. Jumping from one node map to the next is a change of coordinates. When jumping, particles must remain at the same physical location which is described slightly differently by the new node map. Thus, jumping node maps can increase the uncertainty associated with the vehicle's estimated location. For example, consider a vehicle moving in a long straight tunnel as in Fig. 2B. Because there are no longitudinal features from which to localize, noise must be added to the particles after jumping to the next node map in order to prevent divergence.

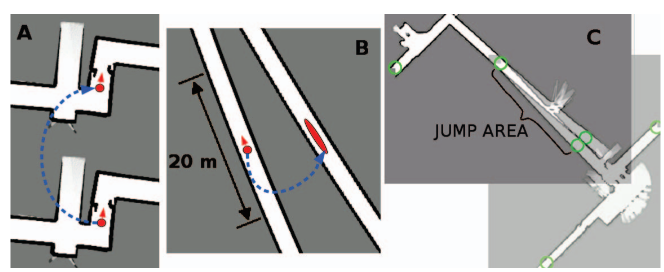

Fig. 2. A: Well defined area—a good place to jump node maps; B: Poorly defined area—hard to figure out exact transformation; C: Node maps overlap—the area where the localization algorithm can jump from one node map to the next.

In order to decrease errors, jump locations can be selected based on the presence of 'wall features', which allows the localization algorithm to quickly decrease the jump error, as shown in Fig. 2A. The following steps summarize how jump locations are determined for each node map:

1. Use the A* search to find a path through the middle of the tunnel from the main RFID to all adjacent RFID tags on the current node map. If an intersection exists in the environment then multiple paths will overlap from the main RFID to the intersection then diverge to each adjacent RFID tag.
2. From each path, remove the overlapping part that is common to multiple paths. The remaining part of the paths lead to exactly 1 adjacent RFID tag each therefore the destination node map is uniquely defined.
3. Find jump points to each adjacent node map.
   (a) At 0.5-m intervals on the remaining path, simulate a laser range finder (by ray-tracing on the map).
   (b) Sort candidate jump locations based on wall features and variance associated with each pose scan.
   (c) Pick the best one and find the transformation that aligns the current node map with the destination node map at the selected location.

To meet the requirements of large-scale localization on a standard computer, a memory management module was developed so that, for any environment and regardless of the total number of node maps, only the current and its adjacent node maps are loaded in memory at any instance in time.

2.3. Global Localization

One advantage for using a particle filter for localization is the ability to do so globally [8]. However, as the size of the map increases more particles are needed to globally localize. Furthermore, the bigger a map, the higher the probability of having multiple locations (tunnels) with very similar scan profiles. This situation can lead to particles converging to multiple likely locations and it may take a very long time to solve the location ambiguity correctly. All of the above may render the particle filter impractical.

The presence of static RFID tags in the environment simply allows for fast global localization when a tag is detected by the vehicle. The vehicle location (but not orientation) is then known with an error equal to the maximum range of the RFID tag reader (in our experiments, a few metres).

To make global localization even more robust, the direction of travel of the vehicle can be estimated from an on-board compass. By comparing the on-board compass data with the node map North direction (estimated during mapping), the heading of the vehicle is obtained. Given our RFID placement convention, the compass accuracy must only be better than $\pm 90^\circ$ in order to solve the direction of travel.

For brevity's sake, mathematical details about the particle filter are not provided here. The reader is referred to [8] or any of many references about particle filters.

3. EXPERIMENTS

The localization system has been tested in two environments: 1) on-line in the Carleton University (CU) underground tunnel network; and, 2) off-line by using data collected in the CANMET Experimental Mine in Val d'Or, QC. In this paper, we have chosen to focus on the on-line results.

3.1. On-line Testing

The CU campus is connected by a network of underground tunnels[1], illustrated in Fig. 3, with an average width of about 4 m. RFID tags were installed in the tunnels by sticking them to the ceiling lights. The distance between consecutive RFID tags ranged from approximately 50 to 250 m. Thus, single node maps had sizes from 150 to 330 m. The chosen resolution of the node map occupancy grids was 10 cm.

Fig. 3. CU underground tunnels and sensor equipped vehicle.

A Taylor-Dunn electric vehicle (Fig. 3) was equipped with two US Digital A2 optical encoders to record the steering angle and wheel rotations, which are used as odometry measurements. A rear-facing SICK LMS 111 laser range finder provided range measurements over a 270° field of view, and an Alien ALR-9650 EPC Class-1, Generation-2 RFID reader was used to sense nearby Alien ALN-9654 EPC Class-1, Gen-2 tags. Digital compass module HMC6352 was used to detect the local magnetic field vector relative to the vehicle pose. A custom real time data acquisition system was used to collect data at a sampling rate of $\sim$20 Hz from the on-board sensors.

An Intel Centrino2 (2.26 GHz) laptop was used to run the on-line particle filter algorithm with an average of 1000 particles at $\sim$10 Hz. The localization algorithms were coded in

[1] See http://www.carleton.ca/campus/ for a topological map.

Python and a front-end Graphical User Interface (GUI), resembling a car GPS unit, was developed such that meaningful information about the vehicle pose and status could be shown in real time to the vehicle operator. A web interface for the localization system, called MineView (www.mineview.ca) was also created so that when the vehicle is in an area with Wi-Fi, it could be used to stream data to a web server that displays the vehicle's live position on a map for remote monitoring.

4. RESULTS AND DISCUSSION

The underground localization system has been successfully tested in many multi-kilometre long runs in the CU tunnel network. Tens of hours have been spent localizing the vehicle at speeds of up to 25 km/h (which is reasonable for underground mining vehicles). The system's GUI is shown in Fig. 4.

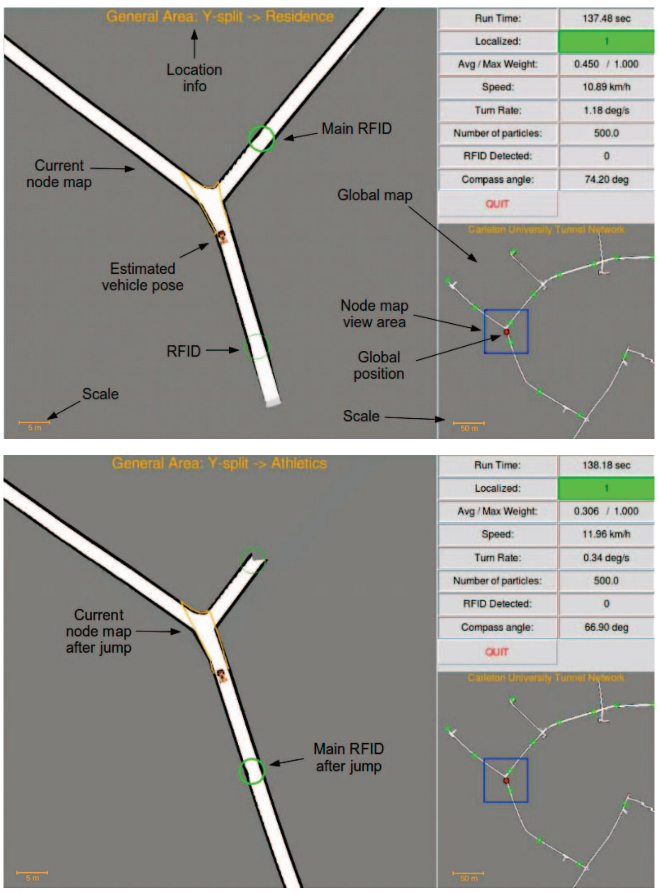

Fig. 4. Screen shot from GUI before and after vehicle jumps node maps while traveling through the CU tunnels.

The localization error inside a node map is composed of two parts: pose estimate error and mapping error. Many factors influence the errors and any objective error measurement test will only be representative for the particular combination of environment, map, vehicle, sensors used, speed driven both for mapping and localization, path driven, wall features, algorithm parameters, floor roughness, etc. Based on a sequence of manual measurements (not described here), a conservative estimate of the current mapping error is up to 5 m in position with up to 5° orientation error per 100 m travelled. Localization error can be as small as 30 cm or as large as a few metres in a long tunnel with straight featureless walls (not common in mining).

In summary, this paper has described a 2D localization system for underground environments using *a priori* maps. The efficient use of RFID node maps for localization allows truly large scale environments to be mapped and localized on with metre-level accuracy using an average computer. A GUI and web interface were designed and tested. Experimental results from on-line localization over kilometre-long runs in the CU underground tunnels have been presented briefly. The authors believe this work has the potential of becoming an enabling technology with many uses in underground mining.

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