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Intelligent based tracking for Underground mining using Fuzzy logic approaches

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Abstract: ***A framework for tracking problems using particle filters (sequential Monte Carlo methods) is developed. It consists of a class of motion models and a general non-linear measurement equation in position. A general algorithm is presented, which is parsimonious with the particle dimension. It is based on marginalization, enabling a Kalman filter to estimate all position derivatives, and the particle filter becomes low-dimensional. This is of utmost importance for high performance real-time applications. Automotive and airborne applications illustrate numerically the advantage over classical Kalman filter based algorithms. Here the use of non-linear models and non-Gaussian noise is the main explanation for the improvement in accuracy. Tracking, where another object's position is to be estimated based on measurements of relative range and angles to one's own position. Based on simulations, we also argue how the particle filter can be used for tracking based on Monte Carlo methods for tracking the objects. Finally, the particle filter enables a promising solution to the tracking. With possible application to robot localization. In future we implement in hardware using RF technology.***

Keywords— Underground communications, wireless propagation modeling, underground mines, tunnels, waveguide models, geometrical optical models.

I Introduction

The mining industry plays a vital role in the global economy. The current estimated market capitalization of global mining companies is about $962 billion [1], [2]. A large portion of these operations are underground and involve specialized equipment and processes. Communication systems play an increasingly important role ensuring personnel safety and optimizing the mining process. The estimated size of underground mining equipment market alone is currently about $45 billion [3], a small but important portion of which is allocated communications systems. The modern era of underground communications began in the early 2000's as the mining industry sought to take advantage of considerable advances in ultra-high-frequency (UHF) technology, especially cellular phones, wireless-local-area-network (WLAN), UWB and radio-frequency-identification (RFID). Although the mining industry is inherently conservative and reluctant to invest in costly new technologies, high profile accidents often prompted regulators to require that the mining (and mining communications) industry devote increasing attention to safety and safety communications [11]. The need to understand and characterize wireless channels has been recognized since the earliest days of wireless communications. The objective of channel characterization or modeling is to capture our understanding of the manner in which the propagation environment impairs and distorts wireless signals in a form useful in the design, test and simulation of wireless systems.

A. Through-The-Earth Communications

Interest in wireless communications for underground mine dates back to the 1920's when the earliest pioneers of radio were interested in the possibilities of TTE wireless trnsmission. N. Tesla suggested to use ELF signals, and the earth as a transmitting medium to send messages across the world in 1899 [20].

B. Through-The-Wire Communications

In the early history of through-the-wire communications in tunnels and underground mines, implementation of communication systems was based on experimental observations without any theoretical insights or empirical modeling attempts.People working in underground mines found that low frequencies on the order of 10 MHz (cutoff frequency of fundamental modes of most tunnels) could cover distances of less than 30 m in an empty mine [26]. However, they also observed that conductors such as electrical cables, pipes and *etc*.,

C. Through-The-Air Communications

TTA is another wireless system for communications in underground mines. It is capable of offering various applications such as two-way voice and data communications, tracking miners and equipment, remote control and sensing, video surveillance and *etc*. In the early 2000's, advances in short-range digital communications to cover 100's of meters motivated the mining industry to consider WLAN off-the-shelf products to support short-range applications in underground. In the late 2000's,the mining industry was attracted to low data rate technologies such as ZigBee, active-RFID (10's of meters), passive- RFID (about 1 meter) and high data rate systems, such as UWB systems, because they offer short-range, low powerand positioning capabilities.

II Related Works

Recent developments have demonstrated that particle filtering is an emerging and powerful methodology for sequential signal processing with a wide range of applications in science and engineering. It has captured the attention of many researchers in various communities including those of signal processing, statistics, and econometrics, and this interest stems from its potential for coping with difficult nonlinear and/or non-Gaussian problems. Based on the concept of sequential importance sampling and the use of Bayesian theory, particle filtering is particularly useful in dealing with nonlinear and non-Gaussian problems. The underlying principle of the methodology is the approximation of relevant distributions with random measures composed of particles (samples from the space of the unknowns) and their associated weights.With particle filtering, continuous distributions are approximated by discrete random measures, which are composed of weighted particles, where the particles are samples of the unknown states from the state space, and the particle weights are "probability masses" computed by using Baye's theory.In the Implementation of particle filtering, importance sampling plays a crucial role and, since the procedure is designed for sequential use, the method is also called sequential importance sampling. The advantage of particle filtering over other methods is in that the exploited approximation does not involve linearization around current estimates but rather approximations in the representation of the desired distributions by discrete random measures The ability to solve the problem of robot localization efficiently will have a tremendous impact on the ways in which robots can be integrated with daily living.These are called proprioceptive measurements, since they estimate the robot's relative motion from onboard sensors rather than measuring from some absolute point of reference. The process of integrating these proprioceptive measurements over time to maintain an estimate of the robot's pose is known as dead reckoning. Dead reckoning localization is easily achieved and can provide high accuracy for short paths. Dead reckoning alone will fail for most real-world applications, however, since it inherently provides no means of correcting error and therefore suffers from unbounded error accumulation.To improve on this, we look for some means to sense the robot's pose absolutely, with reference to a fixed point or points. In this paradigm, localization at any point in time does not require knowledge of the prior positions of the robot, and error in localization is determined only by the noise and bandwidth of the sensors.GPS is a common means of absolute localization. Similarly, our radio frequency beacons, placed in the robot's environment and providing frequent range measurements, could be used to absolutely localize in a way analogous to GPS localization. However, noise in the signal precludes our use of the RF beacons for absolute localization and our dead reckoning measurements are received at a higher bandwidth. Since dead reckoning alone results in unbounded error, we turn to sensor fusion methods to combine our dead reckoning and range measurements to better localize the robot. The absolute range measurements will provide feedback to the dead reckoning, effectively bounding the error.This results in a weakness common to all linear methods -- the Kalman filter will not converge when the initial state is not sufficiently accurate. Based on the concept of sequential importance sampling and the use of Bayesian theory, particle filtering is particularly useful in dealing with nonlinear and non-Gaussian problems. Nevertheless, we will see the Kalman filter localize a robot to, at its best, within an average of 17cm of its true position (Cross-track error).Given the shortcoming of the EKF, we look to some non-linear methods. First, we will examine the sliding batch method, which localizes a window of robot pose estimates and range measurements at one time. The pose estimates are optimized given all the information in that window, then the window slides forward one increment in time and the process repeats. Accuracy for this method is high (about 15cm average cross-track error at its best), but due to its complexity offline processing time is required. We also consider localizing with a Particle Filter, also known as Monte Carlo Localization.In underground mine needs to maintain an accurate estimate of its location to successfully complete its task. Many methods exist for estimating a mobile robot's pose (position and attitude). This method maintains a probability distribution representing the robot's position by maintaining a set of samples (particles) from that distribution. Given an initially uniform distribution, we will see the Particle Filter localize given no initial pose estimate, thus overcoming the EKF's chief weakness. However, we will see that the overall accuracy of our estimate from the Particle Filter is lower than for the EKF (26cm average cross-track error at best), demonstrating a tradeoff between the algorithms.

III Proposed Approach

Systems that can track cars using video from fixed cameras can be used to predict track volume and flow; the ideal is to report on, and act to prevent, track problems as quickly as possible. A number of systems can track vehicles successfully. The crucial issue is initiating a track automatically. In the two systems we describe here, the problem is attacked quite differently. Sullivan et al. construct a set of regions of interest (ROI's) in each frame. Because the camera is fixed, these regions of interest can be chosen to span each lane (figure 1); this means that almost all vehicles must pass directly through a region of interest in a known direction (there are mild issues if a vehicle chooses to change lanes while in the ROI, but these can be ignored). Their system then watches for characteristic edge signatures in the ROI that indicate the presence of a vehicle (figure 2). These signatures can alias slightly typically, a track is initiated when the front of the vehicle enters the ROI, another is initiated when the vehicle lies in the ROI, and a third is initiated close to the vehicle's leaving, because some of the vehicle's edges are easily mistaken for others. Each initiated track is tracked for a sequence of frames, during which time it accumulates a quality score essentially, an estimate of the extent to which predictions of future position were accurate. If this quality score is sufficiently high, the track is accepted as an hypothesis. An exclusion region in space and time is constructed around each hypothesis, such that there can be only one track in this region, and if the regions overlap, the track with the highest quality is chosen. The requirement that the exclusion regions do not overlap derives from the fact that two cars can't occupy the same region of space at the same time. Once a track has passed these tests, the position in which and the time at which it will pass through another ROI can be predicted. The track is finally confirmed or rejected by comparing this ROI at the appropriate time with a template that predicts the car's appearance. Typically, relatively few tracks that are initiated reach this stage .

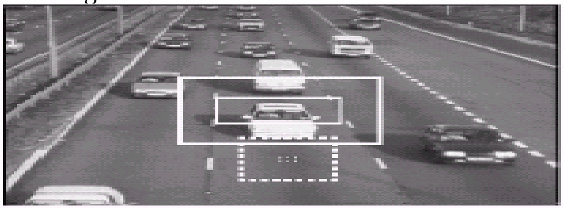

Figure 1: Car tracking

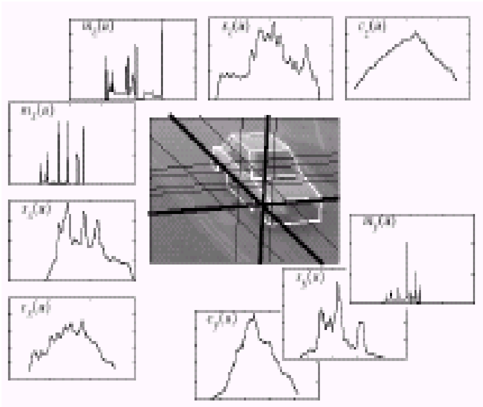

Figure 2: Edge recognition

An alternative method for initiating car tracks is to track individual features, and then group those tracks into possible cars. Beymer et al. use this strategy rather successfully. Because the road is plane and the camera is fixed, the homography connecting the road plane and the camera can be determined. This homography can be used to determine the distance between points; and points can lie together. On a car only if this distance doesn't change with time. Their system tracks corner points, identified using a second moment matrix using a Kalman filter. Points are grouped using a simple algorithm using a graph abstraction: each feature track is a vertex, and edges represent a grouping relationship between the tracks.

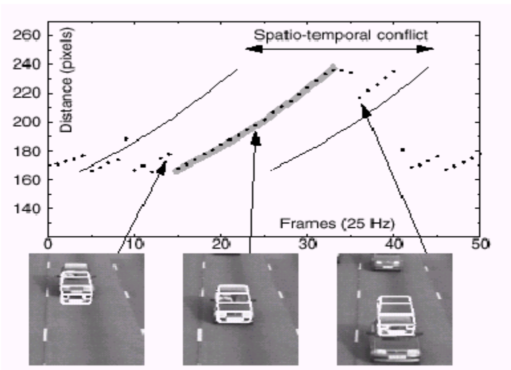

Figure3: ROI

A) Finding and tracking people

Tracking people is difficult. The first difficulty is that there is a great deal of state to a human, there are many joint angles, etc. that may need to be represented. The second difficulty is that it is currently very hard to find people in an image this means that it can be hard to initiate tracks. Tracking People are typically modeled as a collection of body segments, connected with rigid transformations. These segments can be modeled as cylinders in which case, we can ignore the top and bottom of the cylinder and any variations in view, and represent the cylinder as an image rectangle of fixed size or as ellipsoids. The state of the tracker is then given by the rigid body transformations connecting these body segments (and perhaps, various velocities and accelerations associated with them). Both particle filters and (variants of) Kalman filters have been used to track people. Each approach can be made to succeed, but neither is particularly robust. There are two components to building a particle filter tracker: firstly, We need a motion model and secondly, we need a likelihood model. We can use either a strong motion model which can be obtained by attaching markers to a model and using them to measure the way the model's joint angles change as a function of time or a weak motion model perhaps a drift model. Strong motion models have some disadvantages: perhaps the individual we are tracking moves in a funny way; and we will need different models for walking, walking carrying a weight, jogging and running (say). The difficulty with a weak motion model is that we are pretty much explicitly acknowledging that each frame is a poor guide to the next. The configuration to compute a correspondence between pixels in the current image and in the previous image.

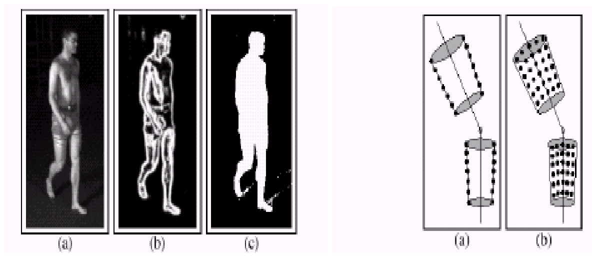

Figure 4: Human tracking

There are three standard approaches to finding people described in the literature. Firstly, the problem can be attacked by template matching; examples include, here upright pedestrians with arms hanging at their side are detected by a template matcher; here walking is detected by the simple periodic structure that it generates in a motion sequence; which rely on background subtraction that is, a template that describes non-people. Matching templates to people (rather than to the background) is inappropriate if people are going to appear in multiple configurations, because the number of templates required is too high. This motivates the second approach, which is to find people by finding faces.

B) Robot localization

In this chapter a different approach to robot localization is discussed. This approach belongs to the class of particle filters. Particle filters are sampling-based methods; the probability density of the state vector is represented by a set of samples randomly drawn from it.First, we look at some of the reasons why sampling-based methods are becoming more popular than the traditional localization methods. Second, the basic particle filter technique for robot localization, Monte Carlo localization, is presented. It seems that although Monte Carlo localization is better than the traditional methods, it also suffers from several problems. Finally the auxiliary particle filter will be described, along with the solutions it offers to the problems of Monte Carlo localization.

C) Motivation

Before describing in detail the workings of particle filters, we look at some of the reasons of why particle filters are preferred over the more traditional localization methods. It seems that by employing this technique several problems concerned with the traditional methods are completely, or the greatest part, solved.

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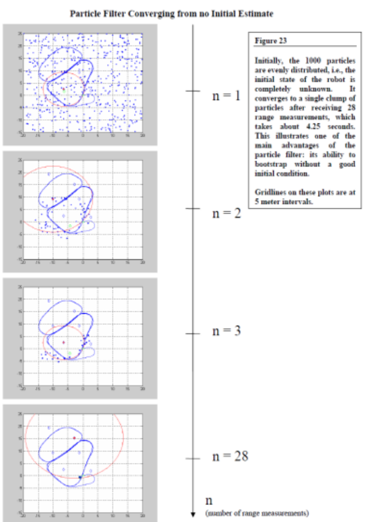
IV. Performance Result

The ability to solve the problem of robot localization efficiently will have a tremendous impact on the ways in which robots can be integrated with daily living. Many tasks for which robots are seemingly well-suited require a high level of precision in localization before such application can occur in the field. For example, a robot delivering mail in an office building, mowing a golf course, or mapping an underground mine needs to maintain an accurate estimate of its location to successfully complete its task. This can be a good localization method over a short distance, but it provides no means of recovering from error that inherently accumulates. So, to maintain a good pose estimate the robot must correct the accumulated error based on data collected from exteroceptive sensors -- for example, landmarks can be visually identified with a camera or detected using sonar or laser scanning. A problem that frequently arises in these forms of landmark identification is that of data association: sensed data must be associated with the correct landmark, even though multiple landmarks may have similar features. Additionally, in many settings it is not possible to guarantee line of sight to the landmarks. In this project. Data for this experiment was collected using an instrumented autonomous robot with highly accurate (2*cm*) positioning for groundtruth using RTK GPS receivers as well as a fiber optic gyro and wheel encoders. Groundtruth position is updated at 100 Hz. his robot was equipped with antennae pointing in four directions and a computer to control the tag queries and process responses. For each tag response, the system produces a time-stamped distance estimate to the responding tag, along with the unique ID number for that tag and the ID of the antenna that received the response. For experimentation, the RF tags are placed atop traffic cones 45.7*cm* above the ground.The robot was driven on a flat, grassy area about 30 meters by 30 meters in size. We distributed 6 RF tags throughout the area, and then programmed the robot to drive in a repeating path among the tags. With this setup, we collected three kinds of data: the ground truth path of the robot from GPS and inertial sensors, the dead reckoning estimated path of the robot from inertial sensors only, and the range measurements to the RF tags. We collected two sets of data; their groundtruth and dead reckoning paths are shown in figure



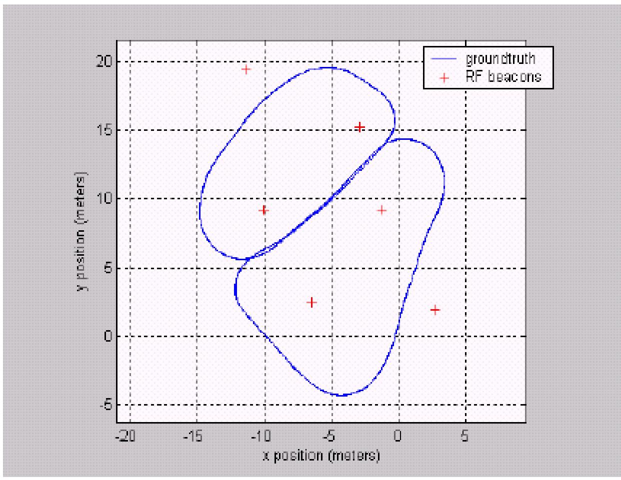


Figure 5: The ground truth path and tag locations

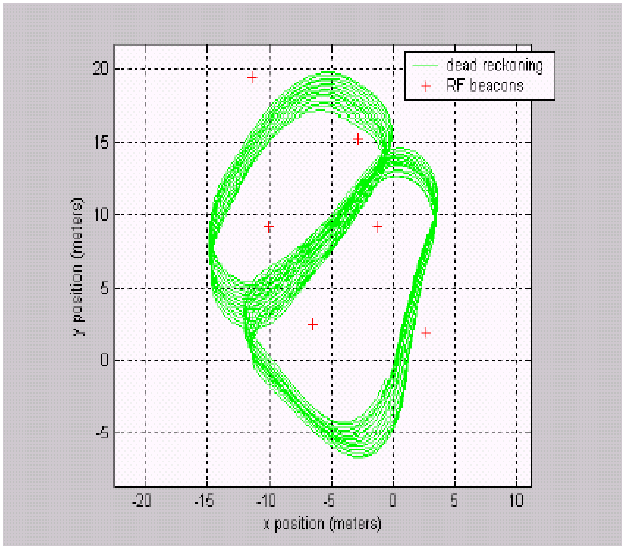


Figure 6:The dead reckoning path estimate and true tag locations

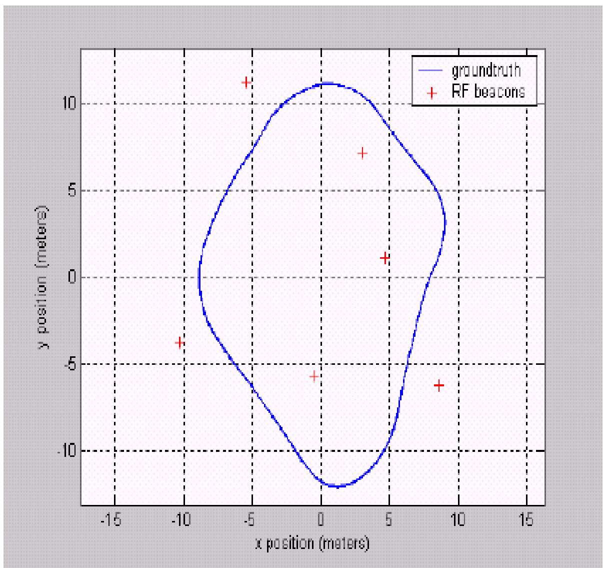


Figure 7:The ground truth path and tag locations for the circular-path dataset.

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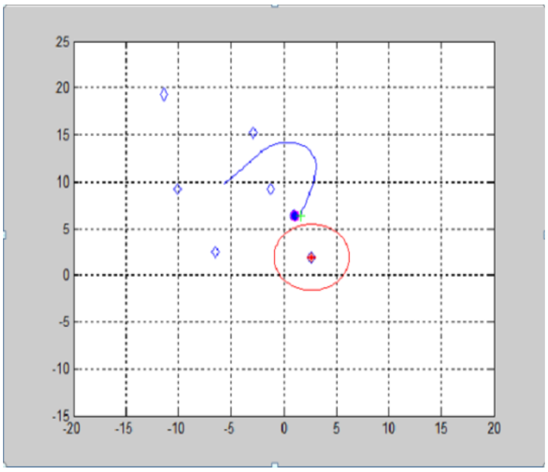

Figure 8: Target tracking

V. Conclusion

In future, we can track the vehicles using the fixed cameras by Map Matching method in real time applications to avoid the collision and also to avoid the traffic jam. We have done the target tracking using particle filters, because particle filter is the best choice for tracking in simulation and real time processes also. In this automating world, everything is automatically controlled. So particle filter is used to track the objects by automatically with the help of systems rather than Kalman filters.

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