A simultaneous planning localization and mapping approach for robust navigation

Alfredo Toriz, René Zapata  
Robotics Department  
LIRMM, UMR 5506 - CC 477  
161 rue Ada, Montpellier - France  
alfredo.torizpalacios@lirmm.fr; zapata@lirmm.fr

Abraham Sánchez, Maria A. Osorio†  
Computer Science Department  
†Chemical Engineering Department  
Benemérita Universidad Autónoma de Puebla  
Puebla, Pue. - México  
asanchez, aosorio@cs.buap.mx

Abstract—This paper presents an algorithm for solving the simultaneous planning localization and mapping (PSLAM) problem, an important key issue for robust navigation in unknown environments. This proposal is a method for integrated exploration, where mobile robot incrementally build a map of this environment while simultaneously use this map to compute the absolute robot localization, and make local decisions on where to move next in order to minimize the error in the estimation of the mobile pose and the configuration locations. The continuous localization process is based on the extended Kalman filter (EK). We present simulated and experimental results on the Pioneer 3DX robot to show the performance of the proposed strategy.

I. INTRODUCTION

Simultaneous localization and mapping is a fundamental and complex problem in mobile robotics research. In this problem, a mobile robot explores and senses an unknown region; besides it constructs a map and localizes itself in the map [2], [12].

The mobile-robot exploration is another research area related to the unexplored region prediction. Exploration is the task of guiding a vehicle during mapping such that it covers the environment with its sensors, i.e., the mobile robot needs to decide the next exploration target that provides the most information gain of an unexplored region. Derived from this concept, the frontier-based navigation method is widely applied to the mobile robot exploration [14]. Many exploration strategies choose the next action on the basis of the above criteria. To improve the frontier-based approach, one can use the approach proposed by Grabowski et al. [6] that provides a better information gain prediction and thus speed-up the exploration process.

The paradigm of integrated exploration was proposed in [10], here, the exploration approach calls for a balanced evaluation of alternative motion actions from the point of view of information gain, localization quality and navigation cost. A randomized method for integrated exploration was proposed by Freda et al. [5], this approach is based on the randomized incremental generation of a data structure called sensor-based random tree (SRT), and has a continuous localization procedure based on natural features of the safe region integrated in the method, i.e., the information gain and localization potential are considered when the algorithm evaluates candidate configurations for exploration. In [4] the authors addressed the problem of how to perform concurrent mapping and localization (CML) adaptively. They proposed a stochastic mapping approach that is a feature-based approach to CML, this approach uses a delayed nearest neighbor data association strategy to initialize new features into the map, matches measurement to map characteristics and delete out-of-date features. They also introduced a metric for adaptive sensing, defined in terms of Fisher information, that represents the summation of areas in the elliptical error of the vehicle and its estimated features in the map.

This work is based on the randomized method for integrated exploration, proposed by Freda et al., [5]. In our method we did not use the feature-based continuous localization scheme, simultaneous update of robot pose and linear features estimates is performed via extended Kalman filtering. Therefore like the original method, our proposal is a frontier-based strategy for the integrated exploration. An important feature of this kind of method is that the optimization of information gain and navigation cost are automatically optimized by the local randomized strategy which proposes candidate destinations [11]. In fact, in the work proposed by Espinoza et al., we extended the original SRT method for different classes of mobile robots [3].

The paper is organized as follows. Section II presents briefly the extended Kalman filter. Section III gives an overview of the integrated exploration method and discuss in detail the associated process. Simulation and experimental results are discussed in Section IV. Finally, the conclusions and future work are presented in Section V.

II. THE EXTENDED KALMAN FILTER

The Kalman filter is the result of an evolutionary process of ideas from many creative thinkers over many centuries. The principal uses of Kalman filtering have been in modern control systems, in the tracking and navigation of all sorts of vehicles, and in predictive design of estimation and control systems. These technical activities were made possible by the introduction of the Kalman filter [7]. Extended Kalman filtering was used in the very first application of Kalman
filtering: the space navigation problem for the Apollo missions to the moon and back. The approach has been successfully applied to many nonlinear problems ever since. Success depends on the problems being quasilinear, in the sense that unmodeled errors due to linear approximation are insignificant compared to the modeled errors due to dynamic uncertainty and sensor noise.

The SLAM process consists of a number of steps. The goal of the process is to use the environment to update the position of the robot. Since the odometry of the robot (which gives the robots position) is often erroneous we cannot rely directly on the odometry. We can use ultrasonic sensors to correct the position of the robot. This is accomplished by extracting features from the environment and re-observing when the robot moves around. An EKF (Extended Kalman Filter) is the heart of the SLAM process. It is responsible for updating where the robot thinks it is based on these features. These features are commonly called landmarks. The EKF keeps track of an estimate of the uncertainty in the robots position and also the uncertainty in these landmarks it has seen in the environment.

The Extended Kalman Filter (EKF) is used to estimate the state (position) of the robot of odometry data and landmark observations. The EKF is described generally in terms of the estimation of the state only (it assumes that the robot is in a perfect map). That is, it does not have update the map that is necessary when using EKF for the SLAM. Most of the EKF is standard, as a normal EKF, once the matrices are set up, it is basically just a set of equations, see [7] for more details.

III. INTEGRATED EXPLORATION

Several techniques have been proposed so far to tackle the SLAM problem [12]. The main difference between them concerns basically the environment representation and the uncertainty description. A wide variety of localization and mapping techniques relies on environment representations consisting of a set of characteristics elements detectable by the robot sensory system (feature-based maps).

SLAM approaches are used simultaneously with classic exploration algorithms. However, the result obtained by the SLAM algorithm strongly depends on the trajectories performed by the robots. Classic exploration algorithms do not take localization uncertainty into account and direct the exploration in order to minimize the distance travelled while maximizing the information gained. When the robots travel through unknown environments, the uncertainty over their position increases and the construction of the map becomes difficult. Consequently, the result can be a useless and inaccurate map. Returning to previously explored areas or closing loops reduces the uncertainty over the pose of the robots and improves the SLAM process.

The SRT method is based on the construction of a data structure called Sensor-based Random Tree (SRT), which represents a roadmap of the explored area with an associated Safe Region (SR). Each node of the tree (T) consists of an odometric estimate \( \hat{q} \) of the robot configuration with an associated local safe region (LSR) S as it was reconstructed by the perception system. A continuous localization process based on the extended Kalman filter (EKF) corrects \( \hat{q} \) and its LSR to obtain a global consistency. T is incrementally built by extending its branches towards zones apparently not explored.

The implemented algorithm is shown in Fig. 1 (this algorithm is inspired by the interesting work proposed by Freda et al., [5]). At each iteration of the algorithm, initially one can obtain the detected position \( q_{act} \) of the robot on which the correction will take part, according to its LSR position. The tree is updated adding the new configuration \( q_{act} \) and the associated LSR.

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INTEGRATED_EXPLORATION(q_{init}, K_{max}, l_{min}, l_{loc})
1  for k=1 to K_{max}
2    \( \hat{q} \leftarrow \text{ODOMETRY}; \)
3    S \leftarrow \text{LSR};
4    (q_{act}, S) \leftarrow \text{LOCALIZE}(\hat{q}, S);
5    T \leftarrow \text{EXTEND_TREE}(q_{act}, S);
6    F \leftarrow \text{FRONTIER}(q_{act}, S, T);
7  if F \neq \emptyset
8    i \leftarrow 0
9    VALID \leftarrow \text{FALSE}
10   While((i < \text{MAX_ITER}) && (VALID))
11     \( \theta_{rand} \leftarrow \text{RANDOM_DIR}(F); \)
12     q_{rand} \leftarrow \text{DISPLACE}(q_{act}, \theta_{rand});
13     VALID \leftarrow \text{VALID_CONF}(q_{rand});
14     i \leftarrow i + 1;
15   end
16   if (VALID)
17     q_{dest} \leftarrow q_{rand};
18     else
19     q_{dest} \leftarrow q_{act}.parent;
20   end
21     q_{act} \leftarrow q_{dest};
22     MOVE_TO(q_{dest});
23 end
24 return T;
```

Figure 1. SRT-based integrated exploration algorithm.

The following step is the processing of the local frontier \( F \), where obstacles and free zones are identified. Generally, \( F \) will be a collection of disjoints arcs. Once obtained these frontiers and if they are free, the procedure RANDOM_DIR randomly generates directions and choose some that are within a free arc, then, a configuration \( q_{rand} \) is generated by taking a step from \( q_{act} \) in the direction of \( \theta_{rand} \). The
size of the step is chosen as a fixed fraction of the radius of the LSR in that particular direction. \( q_{\text{cand}} \) will be collision-free due to the form of \( S \). If no frontier arcs exist, the robot will backtrack to the parent node of \( q_{\text{act}} \) and the exploration cycle starts again.

Once obtained the candidate configuration \( q_{\text{cand}} \), the VALID_CONF procedure would make sure that the new configuration is valid, i.e., this new position is outside of the LSRs of the nodes in other trees. If this new configuration \( q_{\text{cand}} \) is valid, it will be the new configuration destiny \( q_{\text{dest}} \) that the robot will have to reach; on the contrary, if after a maximum number of attempts is not possible to find a configuration \( q_{\text{cand}} \), the parent node of the node \( q_{\text{act}} \) will be the new configuration \( q_{\text{dest}} \) (the robot will backtrack to the parent configuration of the current node \( q_{\text{act}} \)).

\[
\begin{align*}
\text{MOVE}_\text{TO} & \quad 1 \quad \text{while } q_{\text{act}} = q_{\text{dest}} \\
& \quad 2 \quad u_{\text{control}} \leftarrow \text{Best}_U(\text{list}_U, q_{\text{act}}, q_{\text{dest}}); \\
& \quad 3 \quad \text{ROBOT} \leftarrow u_{\text{control}}; \\
& \quad 4 \quad \hat{q} \leftarrow \text{ODOMETRY}; \\
& \quad 5 \quad q_{\text{act}} \leftarrow \text{LOCALIZATION}_EKF(\hat{q}); \\
& \quad 6 \quad \text{end} \\
& \quad 7 \quad \text{return } q_{\text{act}}.
\end{align*}
\]

Figure 2. The MOVE_TO function.

Once the configuration \( q_{\text{dest}} \) is obtained, the function MOVE_TO\((q_{\text{dest}})\), whose description is above will move the robot to this configuration in the following way, it will look among a list of control inputs \((\text{list}_U)\) previously defined, an input \( u_{\text{control}} \) that approximates the robot to the configuration \( q_{\text{dest}} \) from \( q_{\text{act}} \); once obtained, \( u_{\text{control}} \) will be applied to the robot, giving as result, the displacement of the robot to a position near the objective. In this point the odometric position \( \hat{q} \) stored in the memory of the robot will be obtained again, and will be used to obtain the detected position, applying the extended Kalman filter. The algorithm will be repeated until the configurations \( q_{\text{act}} \) and \( q_{\text{dest}} \) are the same.

When there are no more free zones to explore, the robot is forced to backtrack to the root of the tree (start configuration). It is necessary to notice certain aspects of the described algorithm:

- The described method is a general paradigm [5]. Its performance actually depends on the accuracy of the localization process, the LSR reconstruction and the sensors system available.
- The tree \( T \) built plays the role of the global map in this method, it is important to notice that \( T \) is simply the union of all LSRs made consistent with the localization process.
- Local frontier \( F \) is a subsystem of the boundary of the current LSR.

Freda et al. [5] used a sensor-based random tree(SRT). The tree is expanded as new candidate destinations near the frontiers of the sensor’s coverage are selected. These candidate destinations are evaluated considering the reliability of the expected observable features in that points. The tree is used to navigate back to past nodes with frontiers when there are no frontiers present in the current sensor coverage. Furthermore, this method includes a homing operation in order to close the loop at the end of the exploration. However, it does not consider intermediate loop closing or returns to past positions to improve the robot localization.

IV. SIMULATION AND EXPERIMENTAL RESULTS

The integrated exploration based SRT-EKF is evaluated for accuracy and consistency using computer simulations, and for effectiveness using experimental data gathered from different real environments. For our preliminary experiments we used both simulated and real Pioneer P3DX robot equipped with front and rear bumper arrays and a ring of eight forward ultrasonic transducer sensors (range-finding sonar), as shown in Fig. 3. The Pioneer P3DX robot is an unicycle robot. The word unicycle characterizes all types of robots actuated by two independent wheels with one or more floating wheels that assure its stability. The integrated exploration based SRT-EKF has been implemented in our software platform developed at LIRM and dedicated to motion planning and SLAM.

The simulated environment shown in Fig. 4 contains several corridors. The figure also shows the final map (i.e., the map obtained using the proposed SRT-EKF integrated exploration), and the obtained map without localization.

The experimental results are shown in Figs. 5 and 6. The Pioneer robot is driven by two independent wheels, it is an agile, versatile and intelligent mobile robotic platform updated to carry loads in a more robustly way and to traverse sills more surely with high-performance management able to provide power when it’s needed. It has a ring of 8 forward and 8 rear sonars. The 3-DX’s powerful motors and 19cm wheels can reach speeds of 1.6 meters per second and carry a payload of up to 23 kg. Figure 5 shows the final map
Figure 7 shows different views of the execution of the SRT-EKF algorithm in the LIRMM environment.

The Kalman filter (KF) is a technique, derived from the estimation theory that combines the information of different uncertain sources to obtain the values of variables of interest. The filter has been successfully applied in many applications, like missions to Mars, and automated missile guidance systems. Although the concept of the filter is relatively easy to comprehend, the advantages and shortcomings can only be understood well with knowledge of the pure basics and with experience. The EKF has been shown to be successful in many practical nonlinear applications. It particular, it can be used in applications where the model of the system is well described by a linear model, but in which there are some uncertain parameters in the system and measurement models. By treating these parameters as additional state variables the problem can become nonlinear; the parameters then have to be estimated on-line. The convergence properties of the EKF significantly depend on estimating the input and output noise covariance matrices of the process, which have to be appropriately set. In an environment represented by line segments, the line parameters’ covariances comprise the output-noise covariance matrix of the EKF.

V. CONCLUSIONS AND FUTURE WORK

In order for a robot to add its perceptions to a map, it needs to know its location, but in order for a robot to determine its location, it often needs a map. This is one of the central dilemma in robot exploration. Robots often use dead reckoning to estimate their position without a map, but wheels slip and internal linkages may be imprecise. These errors accumulate over time, and the robot’s position estimate becomes increasingly inaccurate. Often map
creation is considered a goal in its own right (the task of exploration). An exploration strategy is then needed to answer the question of where to go next in order to build the map efficiently. Our approach to exploration calls for a balanced evaluation of alternative motion actions from the point of view of information gain, navigation cost, and localization quality. Existing solutions achieve varying degrees of integration between the tasks of localization, mapping and motion control.

We have presented and interesting extension of the randomized method for integrated exploration proposed in [5]. The method builds a data structure through random generations of configurations. The SRT represents a roadmap of the explored area with an associated safe region, an estimate of the free space as perceived by the robot during the exploration. A continuous localization procedure based on the extended Kalman filter of the safe region was integrated in the proposal. The information gain and the localization potential are considered when the strategy evaluates candidate configurations for exploration. Simulations and experimental results on the Pioneer P3DX robot have been presented in this work. We also consider that the localization process is robust, but a way to verify this affirmation is to compare our results with the proposal done by the authors in [5].

The main idea developed in this work, is commonly denoted as integrated exploration or SPLAM (simultaneous planning localization and mapping). With this technique the robot explores the environment efficiently and also considers the requisites of the SLAM algorithm [8]. One can consider a scenario when a mobile robot uses range scans, provided by a 2D laser range finder, to update a map of the environment and simultaneously estimate its position and orientation within the map. The environment representation is based on B-splines features whose parameters are extracted from range scans [13].

As future work we have considered several challenges: an extension of our proposal to the case of integrated exploration with multiple robots, which will take to us to the search of a solution to the multi-robot localization problem; a comparative analysis with the feature-based continuous localization scheme, etc.

REFERENCES


