Mobile Robot Localization using Soft-reduced Hypotheses Tracking

L. Banjanović-Mehmedović*, I. Petrović† and E. Ivanjko†

* University of Tuzla, Faculty of Electrical Engineering, Tuzla, Bosnia and Herzegovina

† University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia

***Abstract*-Mobile robot localization is the problem of determining the pose (position and orientation) of a mobile robot under complex measurement uncertainties. The Soft-reduced Hypotheses Tracking algorithm introduced here is based on the modified multiple model and exploits a soft gating of the measurements to reduce the computational requirements of the approach. The position part is based on an *x*- and *y*-histograms scan matching procedure, where *x*- and *y*-histograms are extracted directly from local occupancy grid maps using probability scalar transformation. The orientation part is based on the proposed obstacle vector transformation combined with polar histograms. Proposed algorithms are tested using a Pioneer 2DX mobile robot.**

I. Introduction

The location awareness is important to many mobile robot applications. Localization techniques can be divided into local position tracking and global localization [1]. Local position tracking provides a new position estimate, given a previous position estimate and new information from proprioceptive and exteroceptive sensors. Kalman filter is the most common solution of the local localization problem. Global localization approach solves the uncertainty in the robot's pose, without initial pose information. It contains also the kidnapped and lost mobile robot problem.

A general framework to represent multiple position hypotheses and to reduce the mobile robot pose uncertainty is that of Markov localization [2]. Markov localization approach can solve those problems because multiple hypotheses are available. However, the accuracy of Markov localization is relatively low [1]. The more complex Multiple-Hypotheses Tracking (MHT) Scheme observes a multitude of different pose hypotheses, but it is difficult for implementation, because a large number of hypotheses may have to be maintained, which requires extensive computational resources. This leads to problems in a real-time implementation. Because of these difficulties, some other algorithms having smaller computational requirements were developed. One of this is Sequential Monte Carlo (SMC*)* or Condensation algorithm. Namely, the methods discussed above are mostly applicable to linear Gaussian state and observation models. As an alternative method for non-linear and/or non-Gaussian models is SMC, which has become a practical numerical technique to approximate the Bayesian tracking recursion. Monte Carlo localization exploits a sample-based method and computation burden of this method is low.

The here proposed **Soft-reduced Hypotheses Tracking (SRHT)** method combines the particle filtering technique with the philosophy behind the probabilistic data association filter PDAF [3]. In order to minimize the computational burden of the particle filter algorithm the number of particles is reduced. This is done by rejection of particles with sufficiently small likelihood values since they are not likely to be re-sampled using a soft-gating (SG) method. The basic idea of SG is to generate new particles that depend on the old state (cluttered measurements) and new measurements, starting with a set of samples approximately distributed according to the best hypothesis from initialization phase. The update step is repeated until a feasible likelihood value is received.

The state estimation problem refers to the selection of a good filter that copes with most of the situations in the application where it would be used. Among the estimation algorithms, the multiple model estimator (MME) is the best-known single-scan positional algorithm and is most widely used for the purpose of tracking maneuvering targets [4]. MME approach computes the state estimate that accounts for each possible current model using a suitable mixing of the previous model-conditioned estimates depending on the current model [5]. Amongst the available multiple models sophisticated techniques the multiple model estimator technique is the best cost-effective implementation and the modified form of this has here been chosen for mobile robot localization application [4].

The localization algorithm in our approach (SRHT) uses a hybrid representation of the environment, i.e. topological map with metric information. The node distances in the topological environment model is 1 (m). Using a combination of SG and modified MME estimator in scope of the implemented localization process, the computational cost is made independent on the size of the environment.

An electronic compass is often used for mobile robot orientation measurement, but it is sensitive to magnetic noise that comes from ferromagnetic objects or structures in the mobile robot environment, from the mobile robot body and the noise produced by its drive system. So it is good to avoid its usage and to develop an algorithm that estimates robot orientation using only sonar measurements. Then histogram-matching procedure given in [6] can be extended to estimate not only position, but also orientation of the mobile robot. While histograms for position tracking (*x*- and *y*-histograms) are extracted from local occupancy grid maps via *Probability*

T. Sobh (ed.), Innovations and Advanced Techniques in Computer and Information Sciences and Engineering, 1–6.

Scalar Transform (PST), polar histograms are obtained via *Obstacle Vector Transform* (OVT) [7]. The result of polar histograms comparison is used for mobile robot orientation correction and is crucial for reliable mobile robot localization when an electronic compass can't be used.

II. LOCALIZATION ALGORITHM STRUCTURE

Block scheme of the proposed localization algorithm is given in Fig.1.

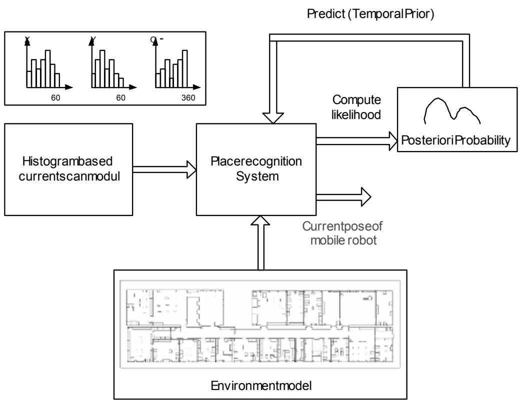

Fig. 1. Block scheme of the proposed localization algorithm.

To build the hybrid map, local occupancy grid maps containing environment metric information are stored at regular intervals of 1 (m). As the robot moves through its environment, sensor readings are obtained and transformed to new form in the *Histogram based current scan module*. Obtained *x*-, *y*- and *angle*-histograms with the pose hypothesis data are then passed to the *Place Recognition System* and matched with the activated hypotheses from the hybrid environment map.

The matching process is performed between an environment hypothesis and predicted hypothesis using the updated previous mobile robot pose. Only few hypotheses with maximum a posteriori probability are activated and updated, giving *predicted value* for the next step. The pose coordinates are updated according to the mobile robot movements measured by the wheel encoders of the mobile robot since the last pose update.

The hypothesis with maximum a posteriori probability within the set of activated hypotheses is considered as the *mobile robot current pose*. In this way, we obtain a reasonably accurate method of tracking the mobile robot pose and global localization of the mobile robot. The number of tracks can become too large in a dense environment. Although the number of associated hypotheses increases exponentially with an increase in the number of updated measurements, it is assumed in this approach that the *number of tracked hypotheses* is $N_T(k) \leq N_V$, where N_V is the number of hypotheses that have to be tracked to achieve an acceptable pose tracking accuracy. From our experimental research we found out that 7 hypotheses fulfill the requirements for safe mobile robot navigation.

Fig. 2 presents large environment E and few clutters C_i, $i = 1, \ldots N_T(k)$, in which mobile robot can be. Whenever the global position of the robot is uniquely determined, the huge state space of the estimation problem can be reduced to a small cube-clutter P centered around the robot's estimated pose.

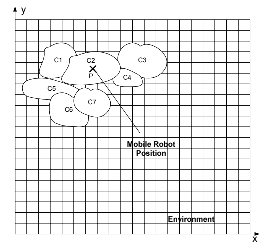

Fig. 2. Clutter centered around the robot's estimated position.

III. HISTOGRAM BASED CURRENT SCAN MODULE

A. X- and Y-histograms

In an occupancy grid map the mobile robot environment is presented with a grid in which each cell holds a certainty value that a particular area of space is occupied or empty [8]. The certainty value is based only on sonar sensor range readings. Each occupancy grid cell in our approach represents an area of 10 x 10 (cm^2) and is considered as being in one of three possible states: occupied (*O*: $P(c_{xy}) > 0.5$), empty (*E*: $P(c_{xy}) < 0.5$) and unknown (*U*: $P(c_{xy}) = 0.5$), depending on the corresponding probability of occupancy for that cell.

Each local grid map, consisting of 60 x 60 cells, is represented by three one-dimensional histograms. Namely, on top of the constructed local occupancy grid we can get three types of histograms: *x*-, *y*- and *angle*-histogram. Both *x*- and *y*-histograms are consisted of three one-dimensional arrays, which are obtained by adding up the total number of occupied, empty and unknown cells in each of the 60 rows or columns respectively (*Probability Scalar Transform*).

Fig. 3.a) presents part of mobile robot environment before applying the Probability Scalar Transformation. Fig. 3.b) presents x and y histogram of current mobile robot scan.

Local Occupancy Grid

0	1	0	0,5	1	0	0,5	0	0,5	0
0	0,5	0,5	0	1	0	1	1	0	0
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0,5	0	0	1	0	0
0	1	0	0	1	1	0	0,5	0	0
0	0,5	0	0	0,5	1	0	0	0	0
1	0,5	0	0	0	0	0	0	0	0
0	1	0	0,5	1	0,5	0	0	0,5	0
0	0	0	0	0	0	0,5	1	0	0

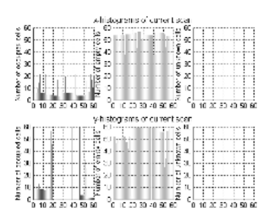

Fig. 3. a) Occupancy grid map; b) *x*- and *y*- histograms obtained from Probability Scalar Transform of current mobile robot scan.