Probabilistic Joint State Estimation of Robot and Non-static Objects for Mobile Manipulation

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Abstract- In this paper, a unified and probabilistic method is proposed for simultaneously localization of a mobile service robot and states estimation of surrounding objects and co-existing people. This method allows intelligent robots to navigate reliably in dynamic environments and provide home-care services based on joint localization results. The algorithm makes use of probabilistic model to represent non-static people and objects states. Moreover, Rao-Blackwellized particle filters (RBPFs) are utilized for efficient joint estimation and laser sensing based smooth observation model is also introduced. The resulting algorithm works in real-time and estimates the position of people and state of doors with sufficient precision. Our approach has been tested in typical indoor environment with people, doors and other non-static objects. Experimental results demonstrate the favorable performance of the position estimation accuracy as well as the capability to deal with the uncertainty of mobile sensing.

Index terms: Intelligent robot, localization, mobile manipulation, laser sensing, particle filters.

I INTRODUCTION

For our aging society, dependable methods to improve service quality for the elderly is a pressing need [1][2]. Among these methods, intelligent robots are believed to be able to function in a human-like way and provide kinds of services for people [3][4][5]. More concretely, mobile service robots are installed in home care environments, endowed with capabilities of a large variety of manipulative or collective tasks [6][7], for example, delivering messages, fetching objects, cleaning rooms, opening doors and so on. Such robots must navigate in dynamic indoor environment with coexisting human as well as interact with objects (e.g., doors, drawers). A major problem to reliable localization of robot and estimating the states of co-existing people and non-static objects is the uncertainty of robot's pose and the ubiquitous sensor noises.

Over the last decade, probabilistic methods have been widely employed in the field of mobile robot localization and navigation. In special situations that robots need to interact with environment, probabilistic methods [9] are of significant importance to deal with the problem of non-static states of environment (including moving people and objects). For example, Limketkai and Biswas [8] et al. use an off-line EM algorithm to differentiate between static and non-static parts of an environment. Hahnel [10] use outlier rejection pre-processing to eliminate the effect caused by moving people. Other researches involve simultaneous mapping of obstacles and moving objects in the SLAM (Simultaneous robot Localization and Mapping) framework. Wang [11] proposes a framework for simultaneous localization, mapping and moving object tracking (SLAMMOT) for outdoor vehicles in crowed urban areas. Stachniss and Burgard [12] maintain clusters of local grid maps corresponding to different observed configurations of the environment.

Mobile manipulation tasks require joint estimation of robot's pose and the states of dynamic objects (and people). For example, in the context of robot taking an elevator or opening a door, robot needs to estimate the state of the door during its navigation for possibly manipulating the doorknob or handler. For another example, when a robot navigates with people, it must estimate the position of people nearby to get prepared for predictive avoidance. In both situations, robot must always precisely locate itself, which is a perquisite of accurate and safe navigation. For joint estimation in the Bayes filtering framework, Rao-Blackwellized particle filters (RBPFs) [13][14][15][17][18][19] provide notable insights into joint estimation tasks such as visual object tracking [14], SLAM [15] and multiple-model tracking [17][18]. In the SLAM cases, RBPFs decompose the joint estimation into two steps as localization with Particle Filter (PF) and mapping with known pose using Kalman Filter (KF) [15] or Unscented Kalman Filter [16]. In [17], the unobstructed motion of a ball is tracked by sampling its motion models resulting from its interactions with the environment.

In this paper, a probabilistic approach to state estimation for simultaneous manipulation and global navigation is proposed. It allows robots to perform many mobile manipulation tasks. The joint estimation algorithm borrow many ideas from SLAM [15] and SLAP [22] research. However, this paper is different from related work [23] in that we extend to consider the localization of both people and non-static objects in a dynamic Monte Carlo Localization framework.

The organization of the lecture is as follows. Section II describes the probabilistic model of robot observation as well as object motion. Section III introduces the proposed joint estimation algorithm based on RBPF. In Section IV, experimental results are given, which illustrates the effectiveness of the proposed method in service robot application.

II Probabilistic Model and Notation

2.1 Representation of States and Environment

We consider sensors based algorithm to determine the pose of robot and the states of dynamic objects (e.g., people and doors) in indoor environments. The position of people are assumed unknown, but the doors are restricted with known positions and unknown states. For example, the shape of a door is governed by a state parameter α that denotes the angle at which the door is open.

At each time step t, the problem of joint state estimation is to recursively evaluate the joint *maximum a posterior* (MAP) distribution, from a *Bayesian* perspective:

$$p(r_t, h_t, \alpha_t \mid z_{1:t}, u_{1:t-1}), \tag{1}$$

where $r_t = (x_{r,t}, y_{r,t}, \theta_{r,t})$ is the robot's pose, h_t represent the robot pose and human position respectively, $z_{1:t}$ is a sequence of measurements, and $u_{1:t-1}$ is a sequence of control it has executed.

Given the robot pose and a new control, the pose evolves according to a probabilistic motion model derived from robot kinematics:

$$p(r_t \mid r_{t-1}, u_{t-1}) \tag{2}$$

The object state evolves according to $p(\alpha_t \mid \alpha_{t-1})$ and the ground-plane movement of people, $p(h_t \mid h_{t-1})$, is assumed to follow a Langevin process [24]. Similarly, sensor measurements are governed by a observation model $p(z_t \mid r_t, h_t, \alpha_t)$.

The environment is presented by an occupancy grid map, following the experience in mobile robot navigation practice. In the occupancy grid map, information about static objects and obstacles in typical office environments such as walls, tables, cabinets are mapped and stored at a resolution of $10\text{cm} \times 10\text{cm}$. However, moving objects (e.g., doors and people) are partial unknown and their states are to be estimated in the joint localization procedure. In the presented paper, we use models comprising polygonal objects ("polygon model") to represent these objects and circular objects ("circle model") to represent people.

2.2 Measurement model

The grids are usually only partially occupied, and thus there is a probability of the laser entirely passing through it. With regard to this, each grid cell is associated with a probability that a laser terminates within it. We assume that the i th robot pose particle is sampled, and thus the laser measurement model with respect to the i th particle is computed as follow.

By comparing the actual laser observation z_t with an ideal laser scan $\{L\}$ ray-traced from the hypothesized robot pose $r_t^{(i)}$, the measurement model $p(z_t \mid r_t^{(i)})$ is computed in which each point is assigned with a probability that is in inverse ratio with its Euclidean distance to the closest object, be it a hypothesized person or a occupied map cell.

To calculate $p(z_t \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M)$ with a prior environmental map M , the person's estimated position $h_t^{(i)}$ and the object's state $\alpha_t^{(i)}$ conditioned on $r_t^{(i)}$, the Likelihood Field Model is computed by fusing three sources of noise:

$$p(z_t \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M) = z_{\text{hit}} p_{\text{hit}} + z_{\boldsymbol{rand}} p_{\text{rand}} + z_{\max} p_{\max} \,. \tag{3}$$

Measurement noise with people hypotheses: p_{hit} captures the sensor noise by a zero-mean Gaussian. The p_{hit} model of the ang_i th laser beam is computed as

$$p(z_{t,ang_i} \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M) = \\ p(dist, \sigma_{hit}) \propto 1/\sqrt{2\pi\sigma_{hit}} \cdot \exp(-\frac{1}{2\sigma_{hit}} d_{ang_i}{}^2), \quad (4)$$

where d_{ang_i} is the Euclidean distance between the ang_i th laser point (after being transformed to the x-y coordinate frame) and the nearest obstacle in the local grid map obtained by the laser ray-tracing. Obstacle candidates can be either mapped objects or person hypothesis.

Failures: The possible failures of the max-range readings are modeled by a point-mass distribution $p_{\max}$.

Unexplained random measurement: The random noise of laser sensors is modeled by a uniform distribution p_{rand}.

For an entire laser scan, the probability $p(z_t \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M)$ amounts to Equation (5) under an independent assumption among the readings of each laser beam

$$p(z_t \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M) = \sum_{ang_i=1}^{N_{ang}} p(z_{t,ang_i} \mid r_t^{(i)}, h_t^{(i)}, \alpha_t^{(i)}, M), \quad (5)$$

in which $N_{ang} = 180$ is the number of laser beams according our laser scan device SICK LMS-200.

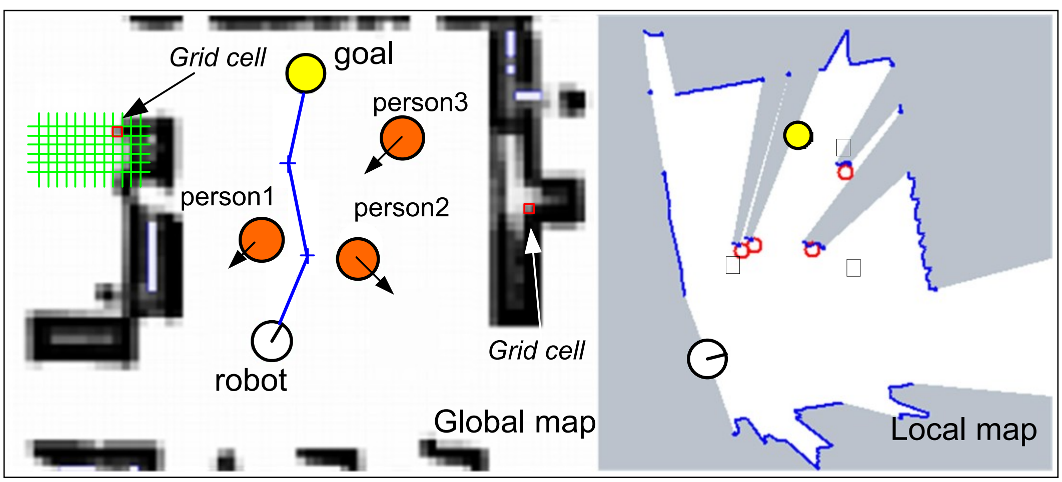


Figure 1. Leg based people-detection using laser range finder

Beside the robot's observation of static obstacles, the measurements about non-static doors and people are considered as "detection driven", i.e., the observation model is valid only when the robot detects the target within the field-of-view of sensors. Thus a leg detection technique

[25] is adopted that models a human leg approximately by cylindrical in laser scans, as shown in Figure 1.

Moreover, a door frame detection technique similar to Chen's method [20][21] is employed which combines visual and range information. In detail, the visual method utilizes robot onboard camera to capture and perceive image data and extract visual cues including intensity edges along the sides (posts) and top (lintel) of the door. When the visual channel reports a valid door detection result (as shown in Figure 2), the laser based observation method mentioned above begins to function in the object(door) state estimation procedure, as will be explained in the following section, which will estimate the angle at which the door is open (illustrated by Figure 3).

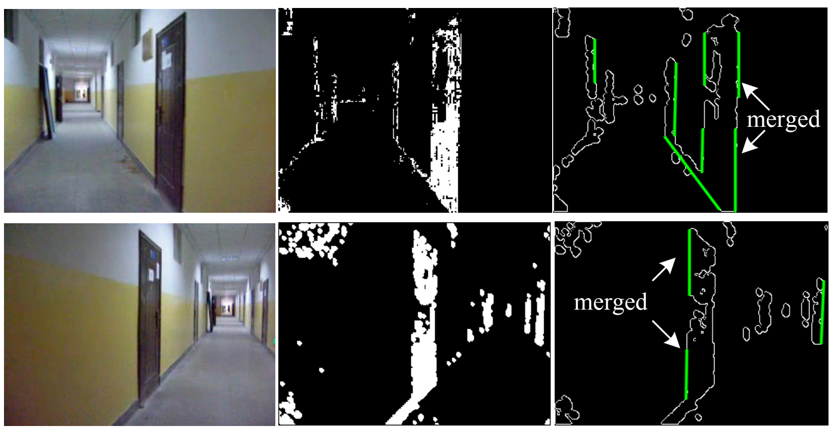


Figure 2. Robot's onboard camera is used for detecting existence of doors

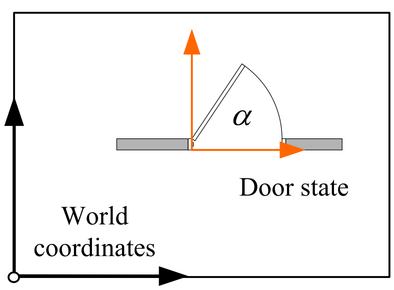


Figure 3. Door state perceived by laser sensor

III Joint Location Inference Using RBPF

3.1 Rao-Blackwellization

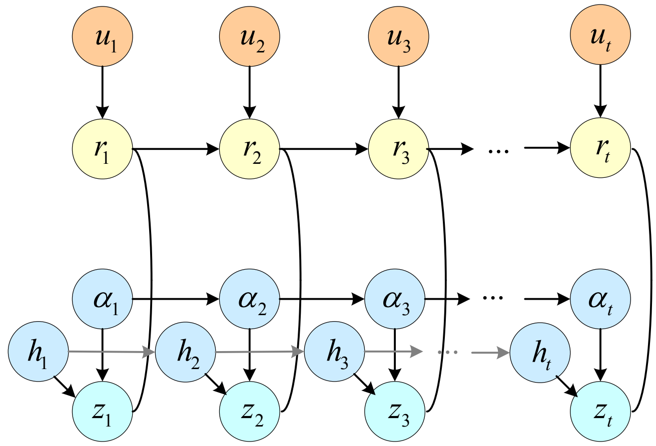


Figure 4. Dynamic Bayesian network model of the robot pose x_t, object state α_t, people position h_t, measurements z_t, and controls u_t.

Figure 4 represents the Dynamic Bayesian network model of the joint localization problem. According to the Rao-Blackwell theorem, instead of sampling full distributions, Rao-Blackwellized particle filters evaluate one part of the filtering equation analytically and the other part by Monte Carlo sampling. Such marginalization replaces the finite Monte Carlo particle set representation with an infinite closed form particle set, which is always more accurate than any finite set.

With an assumption of independent and non-linear movements of people and robots, the RBPF algorithm for SLAP is established on the following factorization of the joint posterior in (1) by conditioning the state h_t and α_t on r_t

$$p(r_t, h_t, \alpha_t \mid z_{1:t}, u_{1:t-1}) = p(h_t, \alpha_t \mid r_t, z_{1:t}) p(r_t \mid z_{1:t}, u_{1:t-1}) . \qquad (2)$$

Since people positions and object states are independent, the above equation can be rewritten as:

$$p(r_t, h_t, \alpha_t \mid z_{1:t}, u_{1:t-1}) = p(h_t \mid r_t, z_{1:t}) p(\alpha_t \mid r_t, z_{1:t}) p(r_t \mid z_{1:t}, u_{1:t-1}) . \qquad (3)$$

Similar to the regular PF, RBPF represents the posteriors by a set of N weighed samples:

$$S_t = \{s_t^{(i)}, w_t^{(i)} \mid 1 \le i \le N\}$$

The key idea of applying RBPF to joint state estimation is to compute (3) by firstly sampling robot pose from $p(r_t \mid z_{1:t}, u_{1:t-1})$ and then computing the state h_t and α_t, respectively, conditioned on each robot sample. This conditioning breaks the high dimensional particles into three sets with lower dimension:

$$S_t = \{S_{r,t}, S_{h,t}, S_{\alpha,t}\} = \{\{r_t^{(i)}, w_{r,t}^{(i)}\}, \{h_t^{(i)}, w_{h,t}^{(i)}\}, \{\alpha_t^{(i)}, w_{\alpha,t}^{(i)}\}\}$$

More specifically, by applying the Sampling Importance Re-sampling (SIR) filter, a Rao-Blackwellized SIR filter incrementally estimates the pose of the robot according to

$$r_t^{(i)} \sim p(r_t \mid r_{t-1}^{(i)}, z_t, u_{t-1})\,. \tag{4}$$

Then the samples of people positions and object states are estimated, respectively:

$$h_t^{(i)} \sim p(h_t \mid h_{t-1}^{(i)}, r_t^{(i)}, z_t)\,, \tag{5}$$

$$\alpha_t^{(i)} \sim p(\alpha_t \mid \alpha_{t-1}^{(i)}, r_t^{(i)}, z_t)\,. \tag{6}$$

To compute (5) and (6), a KF/EFK is attached to each $r_t^{(i)}$ for analytically computing a potential people/object position. Such conditioning turns each conditional people/object state into a Guassian distribution whose mean and variance can be efficiently estimated using KF/EFK.

The RBPF based joint state estimation algorithm is described as follow. After initially drawing N_r uniformity distributed samples from the initial distribution $p(r_0)$, following steps are performed each time when (z_t, u_{t-1}) is available.

Firstly, a sample set $\{r_{t-1}^{(i)}\}, i = 1,..., N_{t-1}$ is drawn from $S_{r,t-1}$, the robot sample set at the time $t-1$ and N_r new samples $\{r_t^{(i)}\}$ are obtained by sampling from the proposal distribution q, chosen as the odometry motion model. In situations of localization with laser range finders, this motion model is a suboptimal proposal distribution since the sensor reading is significantly more precise than the odometry.

Then, the laser observation likelihood field model is computed for robust robot localization in dynamic environment. The new observation model is utilized for the perception update process. The importance weight assigned to $r_t^{(i)}$ can be computed as

$$\begin{aligned} w_t^{(i)} &= \frac{p(r_t^{(i)} \mid z_{1:t}, u_{1:t-1})}{q(r_t^{(i)} \mid z_{1:t}, u_{1:t-1})} \\ &\propto \frac{p(z_t \mid r_t^{(i)}, z_{1:t-1})\, p(r_t^{(i)} \mid r_{t-1}^{(i)}, u_{1:t-1})}{q(r_t^{(i)} \mid r_{t-1}^{(i)}, z_{1:t}, u_{1:t-1})} \cdot w_{t-1}^{(i)}\,. \\ &\propto p(z_t \mid r_t^{(i)}) \cdot w_{t-1}^{(i)} \end{aligned} \tag{7}$$

The second line of (7) restricts the proposal distribution q to a recursive form according to [13] and the third line replaces q by the motion model $p(r_t \mid r_{t-1}, u_{t-1})$.

Thirdly, the improved re-sampling method involves an adaptive re-sampling step to reduce the number of samples to be re-sampled and an Evolution Strategy (ES) based re-sampling step to optimize the distribution [22]. The advantage of the new re-sampling method is that it guarantees the propagation of robot samples to approximate the true distribution of the robot's probabilistic density function (PDF), as well as maintains high computational efficiency. Thus the robustness of the robot localization against dynamic disturbances and environmental cluttering is significantly improved.

Finally, conditioned on each robot sample $r_t^{(i)}$, a conditional position of person is evaluated as Gaussian distribution using EKF. This leads to an unconditional distribution of the person's ground-plane position, approximated by a mixture of N_r Gaussians.

3.2 Human and Object state estimation

A Gaussian/Extended Kalman Filter (EKF) approximation method is used to estimate the object and people states posteriors, $S_{h,t}$ and $S_{\alpha,t}$. In this section, a tracker for estimating the states of objects is taken as an example, and the tracker for estimating the people position is implemented in a similar way. The EKF based object tracker keeps track of the mean μ_t and variance σ_t of the approximating Gaussian in each particle $\alpha_t^{(i)}$. Since $S_{\alpha,t}$ involves only the latest object state α_t rather than the entire state history, the storage and computation loads do not grow with time and thus efficient and real-time computation is guaranteed.

$$\begin{aligned} S_{\alpha,t} &= p(\alpha_t \mid r^t, z^t, u^t) \\ &\propto p(z_t \mid \alpha_t, r^t, z^{t-1}, u^t) p(\alpha_t \mid r^t, z^{t-1}, u^t) \\ &= p(z_t \mid \alpha_t, r_t) p(\alpha_t \mid r^t, z^{t-1}, u^t) \end{aligned} \tag{8}$$

In the above equation, we write z^t and u^t to denote all measurements and controls up to time t. The first step above follows the Bayes rule; the second step follows the conditional independence assumptions [23]. For example, it implies that z_t, the observation at time t, is independent from the history of observations and controls. Finally, the above expression is a product of a measurement likelihood term and an object dynamic model. The observation model is described in Section 2.2, and the object dynamic model is defined as:

$$p(\alpha_t \mid r^t, z^{t-1}, u^t) = \int_{\alpha_{t-1}} p(\alpha_t \mid \alpha_{t-1}) p(\alpha_{t-1} \mid r^{t-1}, z^{t-1}, u^t) d\alpha_{t-1} \tag{9}$$

Equation (9) gives the recursive computation relation of the object dynamics. In the EKF framework, because $p(\alpha_{t-1} | r^{t-1}, z^{t-1}, u^t)$ is already approximated as a Gaussian by a Rao-Blackwellized particle from the previous filtering timestep, the mean and variance of $S_{\alpha,t}$ can be easily computed in closed form using a linear-Gaussian motion model. Similarly, the dynamic model of people is chosen as Langevin process, which can be used in Equation (8) for estimating the mean and variance of people position.

IV Experiment Results

We apply our method to service robots designed for home care applications. An office environment is designed as a test-bed environment to perform home-care services for the elderly and disabled. An ActivMedia Pioneer 3-DX/Peoplebot robot (as shown in Figure 5(a)) equipped with a SICK LMS-200 laser range finder was employed in the experiment. Figure 5(b) shows a situation that human and robot co-exist in the office environment.

(a)

(b)

Figure 5. Service robot employed in the experiment

The occupancy grid map was obtained at 10cm resolution using standard SLAM algorithm with onboard laser sensor. The developed localization software computes in real-time the positions of the robot and moving people and meanwhile estimates the states of doors. The software treats the estimation of people and door states differently. On one side, the people position is maintained in the global world frame of the room directly from the algorithm. On the other side, the door state is recovered by building a single precise polygon model of door and pasting the model onto the grid map at places where doors exist.

Figure 6(a) shows the convergence of samples with the movement of a robot tracking a people. Red (darker) dots and red line denote the sample for approximating the position of the robot and its trajectory history, respectively; Green (lighter) dots and green line denote those of a person. As can be seem from the figure, the samples successfully converged to produce the approximated mean value of the estimated positions.

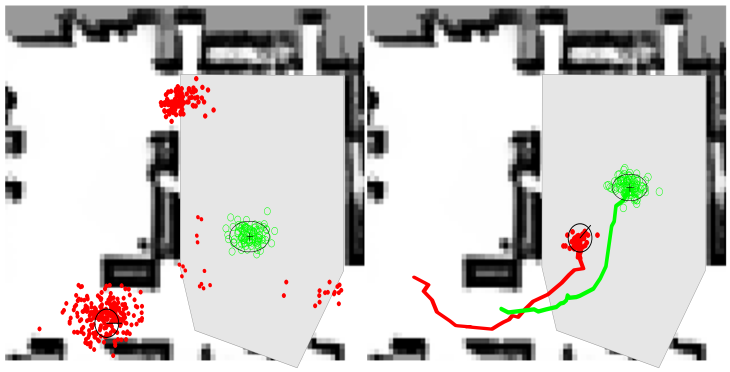
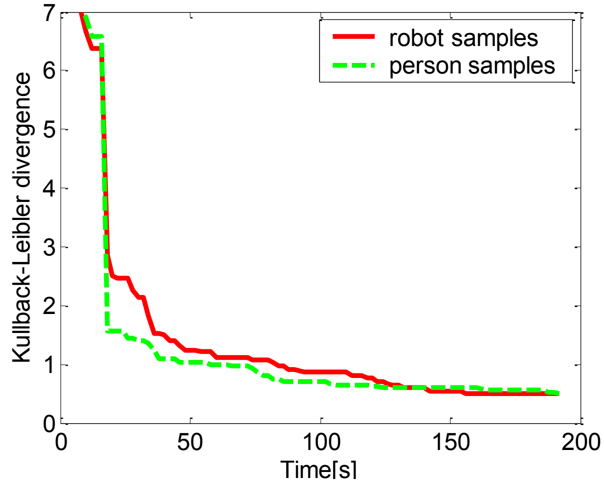
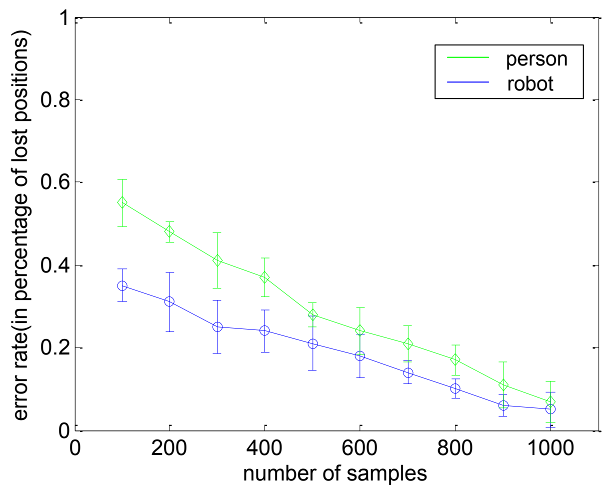


Figure 6. Robot localization with estimation of person position

To give a quantitative evaluation of the localization accuracy, we collected several minutes of laser and odometry data of the robot's approach towards a door in twelve distinct test situations, six of which contains people walking around the robots. The root-mean square (RMS) error with respect to ground truth is taken and the averaged over all twelve test situations reports final accuracy less than 10cm, compared with the whole room environment of $90m^2$ in size. Figure 7(a) shows the evolution of the position estimation error as a function of time. Figure 7(b) shows the statistical relation of the sample number with the error rate, measured in the percentage of time during which the robot lost track of its pose and the person's position. As a compromise between the accuracy and the computational complexity, the number of samples was chosen as 400 to 500 in the experiment. Experimental results yield that the tracking module ensured an average positional error of 6.5cm for robot localization and 3.4cm for people-tracking.



(a)



(b)

Figure 7. Robot localization and people-tracking error

Furthermore, Figure 8(a) shows the global grid map of the whole 4th floor of our laboratory building and the green (lighter) dots demonstrate the laser data layered onto the grid map, which well fit the environment map. Figure 8(b) shows the corresponding laser scan in the robot's local frame. In all, the proposed method can simultaneously estimate the position of robot and coexisting people, as well as the state of other non-static objects, such as doors.

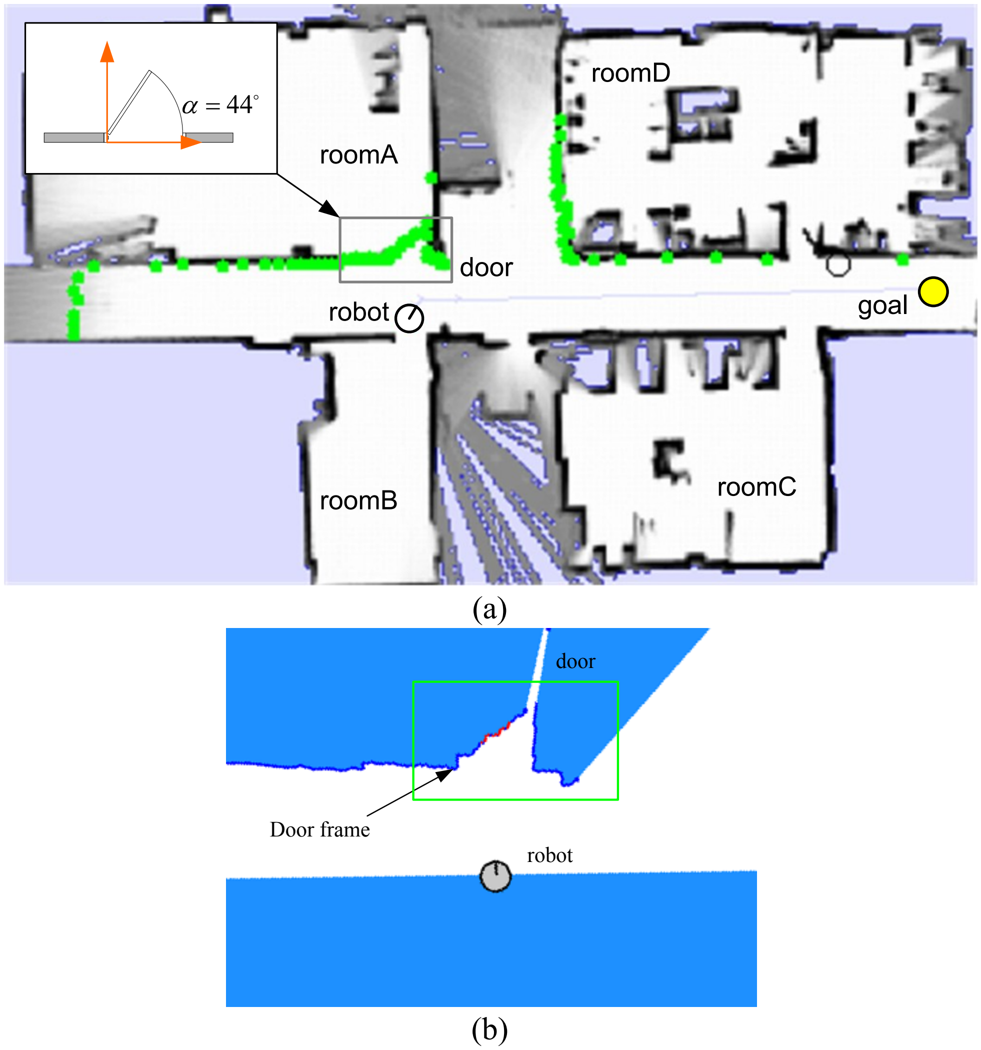


Figure 8. Estimated door state

V CONCLUSIONS

In this paper, a probabilistic method is proposed to jointly estimating of robot location, moving people position and non-static object state. Due to the uncertainty of robot's pose as well as the robot's onboard sensory information, the proposed algorithm makes use of Rao-Blackwellized particle filters to ensure reliable joint localization and tackle with sensor noise and dynamic uncertainty problem. The method allows a single robot to efficiently perform self-localization and object state estimation simultaneously using its onboard sensors. This is considered especially important for mobile manipulation tasks such as taking elevator or opening a door handle. Experiments for mobile robot localization and navigation in typical office environment are given and the experimental results validate the effectiveness of the proposed method.

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