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UWB SLAM with Rao-Blackwellized Monte Carlo Data Association

Tobias Deißler and Jörn Thielecke
Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany.
Email: {deissler, thielecke}@like.eei.uni-erlangen.de

***Abstract*—In situations where the environment is filled with dust or smoke, like in many emergency scenarios, it is still possible to sense the surrounding and build maps by using ultra-wideband (UWB) Radar. This can help firemen and other rescue personnel. In this paper, a method to solve the SLAM (simultaneous localization and mapping) problem is presented. Using UWB radar with a bat-type antenna array consisting of two RX antennas and one TX antenna in the middle, features of the surroundings are detected and used as landmarks for navigation. The main challenge of this approach is the problem of data association, i.e. the task of assigning time-of-flight measurements to corresponding landmarks. The solution presented in this article uses a state space model in combination with a Rao-Blackwellized particle filter.**

***Keywords*—UWB; SLAM; indoor navigation**

I. Introduction

The scenario envisioned in this work is an emergency like an earthquake, fire or terrorist attack that affects a building, where an autonomous vehicle is used to scout the area and help the following rescue personnel to perform their task successfully. To do this effectively, three tasks have to be achieved:

1. Localization: The vehicle has to know where it is.

2. Map building: The vehicle has to build a map of the area to guide human rescue personnel.

3. Object recognition and identification of object features: Special objects of interest to the rescue personnel like unconscious humans or sources of fire have to be identified and located.

Many different approaches to these tasks have been presented e.g. in [1], but the envisioned scenario poses a few extraordinary constraints that impede the use of well-established technologies. First of all, the place of action is probably filled with dust and smoke, so that camera- or LASER-based technologies are not usable. Second, due to the short-term notice of deployment, external infrastructure to help the navigation can not be set up or is likely to be destroyed by the incident. Third, because of the indoor nature of the environment, satellite based navigation systems can not be used reliably.

The solution proposed in this work is based on an ultra-wideband (UWB) radar system with one transmitting and two receiving antennas. This so called bat-type UWB radar array is suitable for this task. The main challenge in this case is data association, the task of assigning the time-of-flight measurements from the radar to corresponding landmarks. A solution is presented in this article using a Rao-Blackwellized particle filter.

The great advantage of the bat-type UWB radar is the fact that it works without a priori knowledge of the surroundings and without any kind of infrastructure. This sets it apart from other means of indoor navigation, for example based on WLAN [2] or RFID [3]. Although those systems do not have to cope with data association, they are not suitable for an emergency scenario. UWB is also a good choice for this task as it can provide additional information like life signs of humans [4], material characteristics [5] or even information about objects inside or behind walls [6]. This work builds upon previously published results that also deal with the bat-type sensor array [7].

The paper is organized as follows: In Chapter 2, an overview of the algorithms, models and methods used is given, with special regard to the characteristics of the bat-type sensor array, the used state-space model and the Extended Kalman Filter (EKF).

Chapter 3 introduces the particle filter and the Rao-Blackwellization used to reduce the dimension of the state space.

Chapters 4 and 5 deal with results and conclusions respectively.

II. Overview

A. Feature Localization Models

To detect and localize features, an UWB radar is used with a bat-type sensor configuration. This sensor array consists of one transmitter (TX) and two receivers (RX1, RX2) aligned with the transmitter in the middle. This bat moves through the environment. Round-trip-times are extracted from UWB impulse responses and used to detect type and location of features in front of the sensor array.

For the features a two-dimensional geometrical model of the real world is used in the algorithm, similar to [8]. Walls are represented as reflecting lines, and edges represent objects with a scattering behavior similar to a point scatterer. Corners are characterized by double reflections at two orthogonal walls. For the three features, the model of the signal propagation paths is outlined in Fig. 1. For walls, the round-trip-time can be calculated by using a virtual sensor array mirrored at the wall. For edges, the round-trip-time is the sum of the distance from TX to the edge and from the edge to RX1 or RX2, respectively. For rectangular corners, the virtual array is obtained by point reflection in the corner.

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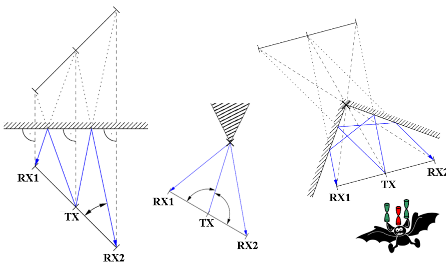

Figure 1. Geometrical propagation path models for walls (left), edges (middle) and corners (right).

It is not possible to distinguish different types of features by one measurement alone. Only by evaluating the peaks in the time-of-flight measurements at different positions is it possible to differentiate between walls, corners or point scatterers and to deduce their location. Those features are then used as landmarks for navigation and to create a feature based map of the building [9].

As can be seen in Fig. 2, the main problem is the fact that in an indoor environment, there are not one, but many reflections from many different features at any given sensor position. Additionally, there are echoes from sources not covered by our propagation models. A working algorithm therefore has to be able to solve the problem of data association, i.e. assigning measurements to the correct features.

B. State Space Model

The basis of the algorithm forms a state space model. It is used in combination with an Extended Kalman Filter to track landmarks and estimate their positions as well as the position and orientation of the robot. The state vector x comprises the robot pose (position in x and y direction as well as the orientation relative to the reference frame). The map is represented as the positions of the N landmarks in two dimensions:

$$x = [x_{robot}, y_{robot}, \varphi_{robot}, x_{landmark1}, y_{landmark1}, \cdots, x_{landmarkN}, y_{landmarkN}]^T . \quad (1)$$

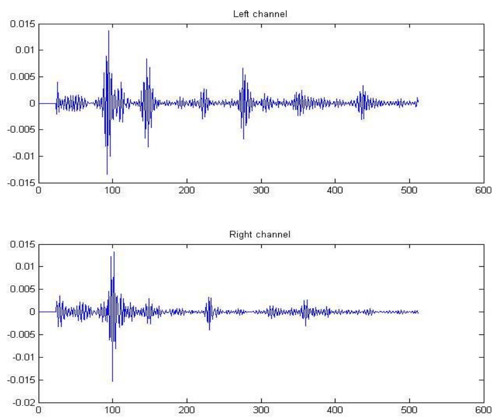

Figure 2. Correlated impulse responses from RX1 (left channel) and RX2 (right channel).

TABLE I.
EXTENDED KALMAN FILTER

New_State_Estimation $(x_{k-1}, P_{k-1}, u_k, \mathbf{z}_k)$:
State Prediction
$x_k^- = g(u_k, x_{k-1})$
$P_k^- = G_k P_{k-1} G_k^T + Q$
State Update
$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R)^{-1}$
$x_k = x_k^- + K_k(\mathbf{z}_k - h(x_k^-))$
$P_k = (I - K_k H_k) P_k^- (I - K_k H_k)^T + K_k R K_k^T$
return x_k, P_k

The estimation of the state vector is predicted and updated using the previous state estimation x_{k-1}, the control data of the robot u_k and the measurements of the UWB radar z_k in the standard fashion of the EKF algorithm, as can be seen in Table I. P denotes the error covariance matrix. The function $g(\ )$ calculates the a priori state estimation from the estimation of the last iteration step and the control data, the function $h(\ )$ is the measurement function that calculates the predicted measurement from the a priori state estimation. G_k and H_k are the Jacobian matrices of $g(\ )$ and $h(\ )$ at time step k. The covariance Q of the uncertainty introduced by the state transition and the covariance R of the measurement noise are assumed to be constant.

C. Data Association

There are two ways to associate the measured time-of-flight values with already observed landmarks: The Nearest Neighbor Data Association and the Probabilistic Data Association.

In the first setup, the Nearest Neighbor Data Association is used to determine the pair of measurements that has the highest probability of belonging to an already observed landmark. For one receiver channel, the correlation variable c_i denotes which measurement z_i is assigned to a landmark j. Note that z_i is the i-th time-of-flight value from the measurement vector $\mathbf{z}$ at time k. To avoid confusion, the subscript k is omitted in the following text. Everything takes place in one time step.

Thus, for each landmark j the probability

$$p(z_i \mid x^-, c_i = j) \quad (2)$$

has to be maximized.

The algorithm is depicted in Table II. For any given landmark in the state vector the predicted measurement is calculated using the measurement equation $h(\ )$ of the Extended Kalman Filter. Then, the predicted measurement is compared to the actual measurements acquired from the

TABLE II.
NEAREST NEIGHBOR DATA ASSOCIATION FOR ONE CHANNEL

```
Calculate_Data_Association (x_k,P_k,z_k):
For all landmarks j stored in x_k
        calculate predicted measurement h_j
        for all real measurements z_i
                calculate distance d_ij between h_j and z_i
        endfor
        d_ij,min=min(d_ij)
        if d_ij,min <threshold
                set c_i=j
        else
                set c_i=0
        endif
endfor
return c
```

UWB radar. A Gaussian distribution and no a priori knowledge about the associations are assumed. Therefore, the measurement with the smallest Mahalanobis distance to the predicted measurement has the highest probability of belonging to that particular landmark and is associated with it. To prevent associations with measurements that are way off, the distance has to fall below a predetermined threshold. This procedure is done for both the left and the right receiver channel.

This method has the advantage of being straight forward. The Mahalanobis distance depends on the uncertainty of the robot and landmark position. This information is available in the error covariance matrix P of the EKF. So, with higher uncertainty, bigger distances are allowed, and with lower uncertainty, the valid range of measurements decreases.

The disadvantage of the Nearest Neighbor method is that incorrect associations due to measurement and estimation errors can not be coped with. This worsens in environments with high noise, false measurements and in cases where the echoes from different landmarks are close to each other.

In contrast to the Nearest Neighbor method, the probabilistic method does not simply choose the association with the highest probability. Instead, for all measurements z_i an importance distribution

$$\pi_j(i) = p(z_i \mid x^-, c_i = j)\, p(c_i = j) \tag{3}$$

is calculated and normalized, again assuming a Gaussian distribution with known covariance. From this distribution the data association vector $\boldsymbol{c}$ is drawn by Monte Carlo methods. In this way, even in the case of false measurements being closer to the predicted measurement than the correct measurement, there is a chance that the right one is chosen. It is important to note that the opposite case – a false measurement chosen over a correct one – is also possible. The reason behind the Probabilistic method is explained in the following chapter.

III. PARTICLE FILTER FOR DATA ASSOCIATION

A. Basic Particle Filter

In the previous chapter, the probabilistic method of data association was introduced. On itself, this method has no advantage over the simple Nearest Neighbor method. Using the Monte Carlo method even produces slightly worse results than simply choosing the association with the highest probability. The Probabilistic method only makes sense if not only one state is estimated, but many hypotheses of possible states. That is what the particle filter is for.

The particle filter is a method for state estimation where the probability density is not represented in parametric form but is approximated with a set S of L samples – called particles. This is particularly useful for non-Gaussian multimodal distributions that can not be estimated with Kalman Filters.

Each particle $s^{(l)}$ in this set S consists of a sample from the state space $x^{(l)}$ and a weight $w^{(l)}$ that indicates the quality of the sample in regard to the real measurements.

$$s^{(l)} = \left[x^{(l)}, w^{(l)}\right]^T \tag{4}$$

The first step of the particle filter works similar to the Kalman filter. In the equivalent of the prediction step, in time step k for each particle $s^{(l)}$ a new sample state estimation $x_k^{(l)}$ is drawn based on the previous sample state $x_{k-1}^{(l)}$ of the particle and the robot control data u_k. Since this is a random process, even if we start from a precisely known state, i.e. all starting samples are the same, the sample states diverge over time, based on the uncertainty of the state update model.

There is no update of the state vector like in the Kalman Filter. Instead, the real measurements $\mathbf{z}_k$ are used only to estimate how close to reality the state sample of each particle is. This is done by assigning a weight to each particle. This weight is also dependant on the old weight $w_{k-1}^{(l)}$ and is updated as

$$w_k^{(l)} = w_{k-1}^{(l)}\, p\left(z_k \mid x_k^{(l)}, c_k^{(l)}\right). \tag{5}$$

The weight also serves as a kind of memory about how good the state estimate fitted in previous iterations. If a particle weight becomes zero, it will not contribute to the approximation of the probability density any more, and particles with a very low weight do not contribute much. It is therefore advised to calculate the effective particle number

$$N_{eff} = \frac{1}{\sum_{l=1}^{L} \left(w_k^{(l)}\right)^2}. \tag{6}$$

and perform a resampling of the whole particle set if it drops below a certain fraction of L. This way, useless

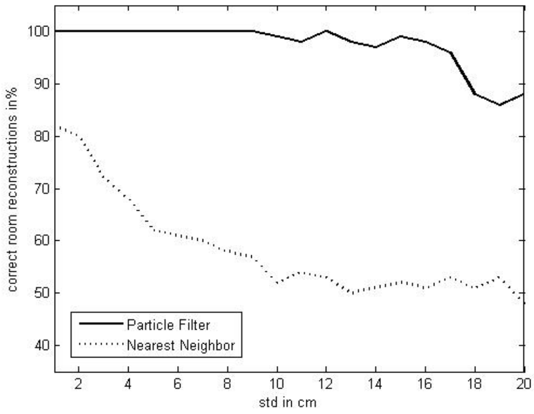

Figure 3. Percentage of correctly reconstructed environments

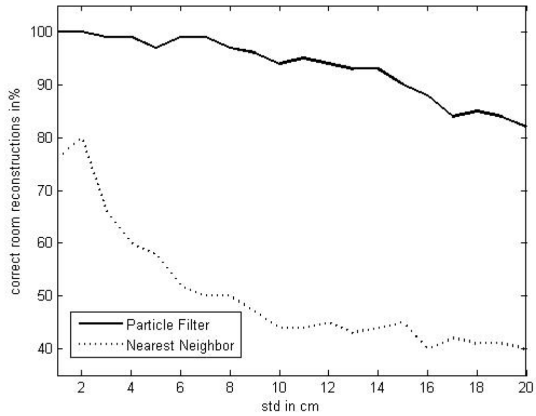

Figure 4. Percentage of correctly reconstructed environments with 10% false measurements

particles are eliminated and the overall quality of the estimation is improved.

B. Rao-Blackwellization

One of the biggest problems in regard to the particle filter is the fact that to approximate a probability density, the number of samples needed increases exponentially with the number of dimensions of the state space. Although it is possible to use a particle filter to estimate a state vector like in (1), it is hardly practical to do in real-time.

In order to reduce the computational burden, it is possible to reduce the number of dimensions that have to be estimated with the particle filter. In the case presented here, the particle filter is only used for data association. Estimates of the state are calculated using the Extended Kalman Filter presented in Chapter II, not drawn randomly like in the basic particle filter. The resulting filter is known as Rao-Blackwellized Particle Filter (RBPF) [10].

Here, each particle $s^{(l)}$ comprises the state estimation $x_k^{(l)}$ and the error covariance matrix $P^{(l)}$, both used in the EKF. The correlation vector $\boldsymbol{c}^{(l)}$ contains the actual data association, and the weight $w^{(l)}$ quantifies how good the hypothesis matches the reality of the measurements:

$$s^{(l)} = \left[x^{(l)}, P^{(l)}, c^{(l)}, w^{(l)}\right]^T \tag{7}$$

In each step, for every particle the following quantities are computed: The new state estimate and the estimated measurements are calculated based on the old one using the basic EKF equations as presented in Table I. The data association is done with the probabilistic method. Here, a Monte Carlo method to assign the measurements actually makes sense. Because of the randomness of the process, the chance is high that at least in some particles the correct association is chosen. These particles are more likely to survive the weighting and resampling step, thus leading to a better reconstruction of the environment.

New landmarks are also introduced on a per particle basis. Measurements that are not associated with already observed landmarks have a chance to be assigned to a new landmark. The type of the landmark is chosen randomly. Since particles with the correct landmark type better match the measurements of consecutive steps, they also tend to propagate through the resampling step.

IV. Tests and Results

The algorithm was tested using simulated data as well as real data acquired with the help of the University of Duisburg-Essen. In the latter case, a Meodat [11] UWB evaluation kit was used and the robot pose was taken with a mechanical positioning system that works with negligible error. The position uncertainty was added artificially in a later step. To account for the probabilistic nature of the RBPF, numerous test runs were conducted for each noise level. First results are shown in Fig. 3. The percentage of correctly reconstructed rooms for the simple test scenario plotted against the position uncertainty. A room reconstruction counts as correct if at the end of the measurement process, the detected landmarks fall within 10 cm of the actual position. Rotation and translation of the reference frame is not taking into account, only the relative position of the landmarks.

The RBPF (solid line) with 100 particles is significantly better than the NN (dotted line). In Fig. 4, every 10th measurement is replaced by artificially created false measurement, which still leads to acceptable results.

V. Conclusion

In this work it was shown that a bat-type UWB radar is an appropriate tool for reconstructing an indoor environment. The different propagation characteristics of walls, corners and edges can be used to distinguish and locate those features and use them as landmarks for navigation.

The problem of data association was handled with a particle filter. Although using N particles requires approximately N times more computational power than the simpler Nearest Neighbor algorithm, due to Rao-Blackwellization the number of particles can be reduced so it is still fast enough to allow for real-time applications. Experiments show that it is better than the NN in terms of reconstruction quality and has a better ability to cope with false measurements, because multiple hypotheses are tracked simultaneously and incorrect reconstructions can be discarded by the algorithm.

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