Ultra-Wideband Based Dynamic Target Tracking Using Cost-Reference Particle Filtering

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Abstract— In this paper, we assess the performance of a sequential Monte Carlo based filter called Cost- Reference Particle Filter (CRPF) in comparison to Extended Kalman Filter (EKF) and Hyperbolic Positioning (HP) based on the time difference of arrival approach for dynamic target tracking. Our results show that CRPF performs better than EKF which in turn performs better than HP. The paper highlights the robustness of CRPF to model inaccuracies which are common in most practical filter implementation problems. The findings of the paper suggest that usage of the CRPF is a promising technique to tackle the problems of random dynamic systems with unknown statistics in ultra-wideband based localization techniques in challenging indoor environments.

Keywords: CRPF; EKF; Dynamic; Localization; Indoor positioning; UWB.

I. INTRODUCTION

The Ultra-Wideband (UWB) technology provides an opportunity for highly accurate localization in challenging indoor environments. Several filter algorithms have been proposed till date to obtain highly accurate and computationally feasible position estimation methods that could be used to further improve the accuracy of UWB localization systems. Among these proposed filters, Bayesian filters have been very popular and are widely used in position estimation approaches [1]. When the system under consideration is linear with Gaussian probabilistic model, the basic Kalman filter gives optimum solution [2]. However, when the system is non-linear, performance of Kalman filter degrades and then filters like Extended Kalman Filter (EKF), Unscented Kalman Filter or Sigma Point Kalman filter come into play. These filters perform well when system is non-linear and the noise distribution is Gaussian but still proper tuning of covariance of the assumed probabilistic model is necessary.

For non-Gaussian noise distribution sequential Monte Carlo based filters like particle filters are gaining importance. They are more robust than Kalman filters but are computationally more expensive [3]. Moreover, they need proper specification of the probability distribution model which might be unknown in many practical applications such as UWB localization systems. For such cases, these filters have to make assumptions of models and if these assumptions differ significantly from the true model, their performance gets highly degraded. Therefore, it is important to have a filter which is more robust and has wider acceptance in terms of application scenarios.

CRPF has emerged as one of the most robust filtering algorithms to deal with the uncertainties of the model. This filter does not make any assumption about the distribution and simply propagates the particles based on a user defined cost function [4]. In this paper we compare the performance of CRPF with both EKF and Hyperbolic Positioning (HP) [5] using the Time Difference of Arrival (TDoA) approach.

Our results show that Root Mean Square Error (RMSE) for estimated trajectory for CRPF is 11.54 cm, EKF is 13.34 cm and HP is 19.57 cm. There is 13.50% improvement in performance in case of CRPF compared to EKF and 41.03% compared to HP.

II. LOCALIZATION PLATFORM ARCHITECTURE

Our UWB localization platform, developed at Fraunhofer IIS in Nuremberg, consists of a static (or moving) tag and a set of static UWB localization receiver anchors. The tag is composed of custom built UWB pulse generator which produces pulse of a full width at half the maximum of 240 ps [6] and an UWB omnidirectional transmit antenna operating in 2-11 GHz band. The receiver part consists of four anchors and one real-time oscilloscope. As shown in Figure 1, each anchor consists of an UWB antenna, a high pass filter and two low noise amplifiers. The LeCroy SDA 816Zi real-time oscilloscope with a 16 GHz analog bandwidth was used as a signal processor. The UWB signals were received by UWB SkyCross SMT-3TO10M-A antennas operating in 3-10 GHz band and then filtered by Mini-Circuits VHF-3100+ high pass filters with a 3.1 GHz cut off frequency. Next, the received signals were amplified through the use of two amplifiers (in each of four channels): Mini-Circuits ZVA-138+ and Mini-
Circuits LE-39+, respectively. The graphical user interface developed in Visual Basic and running on the oscilloscope executed the energy detection receiver algorithms and position calculation functions [7]. In order to enable localization without synchronization between the tag and the receiver, HP algorithm based on TDoA method was implemented.

![Image](image.png)

**Figure 1.** The high level block diagram of the developed UWB localization platform

### III. HYPERBOLIC POSITIONING

The HP algorithm obtains an exact solution for 3D location of an UWB tag given:

- the locations of four fixed receiver anchors
- the signal Time of Arrival (ToA) from the UWB tag to each receiver anchor

The approach of the method consists of following two steps:

- the difference in ToA of an UWB tag at multiple pairs of receiver anchors is calculated to find the TDoA
- each TDoA measurement yields a 3D hyperbolic curve along which the UWB tag may be positioned

### IV. BAYESIAN FILTERING

Optimal filtering, or Bayesian filtering, addresses the problem of estimating the state of a time-varying system that can be observed by measurements [8]. Let us consider a discrete time Dynamic State Space Model (DSSM) consisting of hidden state \( x_k \) with initial distribution \( p(x_0) \) that evolves over time (\( k \) is the discrete time index) as a first order Markov process according to conditional probability density \( p(x_k | x_{k-1}) \). Observations \( z_k \) are conditionally independent and generated according to probability density \( p(z_k | x_k) \).

This DSSM can be expressed by:

\[
x_k = f_{k-1}(x_{k-1}, v_{k-1})
\]

(1)

and

\[
z_k = h_k(x_k, w_k).
\]

(2)

The problem is to recursively estimate the posterior Probability Distribution Function (PDF) \( p(x_k | Z_k) \) starting from initial known density \( p(x_0) = (x_0 | z_0) \). \( Z_k = \{z_1, z_2, z_3 \ldots z_k\} \) is sequence of available observations up to time step \( k \). Now the prediction and update is done in the following two steps.

#### A. Prediction (Time Update)

The previous posterior PDF \( p(x_{k-1} | Z_{k-1}) \) is projected forward in time using the probabilistic model of process equation:

\[
p(x_k | Z_{k-1}) = \int p(x_k | x_{k-1}) p(x_{k-1} | Z_{k-1}) d x_{k-1}.
\]

(3)

#### B. Update (Measurement Update)

At time step \( k \), when the measurement \( z_k \) becomes available, the new posterior PDF is obtained by updating the PDF obtained in (3) with the new measurement by making use of the Bayes’ rule. Estimating the posterior after the observation \( z_k \) becomes available, the posteriori estimate becomes

\[
p(x_k | Z_k) = \frac{p(z_k | x_k) p(x_k | Z_{k-1})}{\int p(z_k | x_k) p(x_k | Z_{k-1}) d x_k}.
\]

(4)

where, \( p(x_k | Z_{k-1}) \) is the predictive density, \( p(z_k | x_k) \) is the likelihood given by the observation model, and \( \int p(z_k | x_k) p(x_k | Z_{k-1}) d x_k \) is the normalizing constant.

Kalman filter is an optimal (with respect to minimum mean square error) recursive filter that estimates the state of a linear dynamic system from a series of noisy measurements where noisy refers to white noise. For the case of nonlinear functions, the multidimensional integrals involved in (3) and (4) are typically intractable. Several different approaches which address nonlinear problems like the Extended Kalman Filter, Unscented Kalman Filter, or Sequential Monte Carlo methods have been seen.

### V. COST-REFERENCE PARTICLE FILTER

Another type of Sequential Monte Carlo (SMC) filter, known as CRPF which does not make any assumption about the probabilistic model of the system has been introduced [9]. The idea here is to propagate the particles from one time epoch to the other based on some user defined cost function. Thus the new method has the advantage of robustness and ease of design. The main aim is to estimate state \( x_k \) for \( k = \{1, 2 \ldots k\} \) according to some reference function that yields a quantitative measure of quality. The cost function \( C(x_{o,k} | z_{1:k}, \lambda) \) is given by recursive structure:

\[
C(x_{o,k} | z_{1:k}, \lambda) = C(x_{o,k-1} | z_{1:k-1}, \lambda) + \Delta C(x_k | z_k),
\]

(5)

with the forgetting factor \( \lambda \) between 0 and 1. If \( \lambda \) is 0, then only the present observation is considered while if \( \lambda \) is 1, then equal weight is assigned to all previous and present observations. Here, \( \Delta C \) is the incremental cost function. The above defined cost function is the simplest form of cost function however it depends on the application and may be modified. A high value of cost function means that the state \( x_k \) is less accurate estimate of given observations \( z_k \). The cost function is recursive in nature and the cost up to \( k - 1 \) can be updated with the knowledge of state and
observation at time step $k$. The risk function described by
\[ R(x_k | z_k) = \Delta C(f(z_{k-1}), z_k) \] (6)
is the prediction of the cost increment $\Delta C(x_k | z_k)$. It measures the suitability of state vector at time step $k$ given the new observation $z_k$. Both the cost and risk function should be strictly convex in range of state $x_k$, easy to implement and dependent on the complete state and observations. A simple choice of cost increment $\Delta C(x_k | z_k)$ and risk function $R(x_k | z_{k+1})$ can be:
\[ \Delta C(x_k | z_k) = \| z_k - h(x_k) \|^q, \] (7)
and
\[ R(x_k | z_{k+1}) = \| z_{k+1} - h(f(x_k)) \|^q, \] (8)
with $q \geq 1$.

The sequential CRPF algorithm consists of:
- particle initialization
- Recursive update:
  - particle selection
  - particle propagation
  - estimation of state

VI. MEASUREMENTS

As a measurement site, a test room at the Fraunhofer Institute IIS in Nuremberg was chosen. Measurements were performed within a test room of 4 m x 9 m area with four receiver anchors in the corners of measurement site, refer Figure 2 and Table I. As a true position of the receiver anchors, fiducial marks on the receiver antennas were chosen and as the true position of the tag, the phase center of the transmit antenna was chosen. The positions of receiver anchors were determined with the use of Nikon iGPS laser measurement system with a typical accuracy of 200 μm. During measurements the tag and transmit antenna were placed on the train moving on the rail road. The number of measurement laps was four. The state vector $x_k$ at time step $k$ as shown by (9) consists of six elements: positions $p_x, p_y, p_z$ of measurement tag and the velocity $v_x, v_y, v_z$ along $x, y$ and $z$ axis respectively,
\[ x_k = [p_x, p_y, p_z, v_x, v_y, v_z]^T. \] (9)

Using a constant velocity model [10], the state equation at time step $k$ is given by:
\[ x_k = T_x x_{k-1} + v_{k-1}, \] (10)
where, $T_x$ is the state transition matrix and $v_{k-1}$ is the usual state noise sequence. The measurement vector $z_k$:
\[ z_k = [z_1, z_2, z_3, z_4]^T \] (11)
is composed of four TDoA values. The differences between pairs of value in the measurement vector is used to calculate the TDoAs used in positioning equations.

<table>
<thead>
<tr>
<th>Anchor</th>
<th>x(cm)</th>
<th>y(cm)</th>
<th>z(cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.</td>
<td>14.0</td>
<td>-53.0</td>
<td>241.0</td>
</tr>
<tr>
<td>B.</td>
<td>413.0</td>
<td>-6.0</td>
<td>51.0</td>
</tr>
<tr>
<td>C.</td>
<td>390.0</td>
<td>944.0</td>
<td>243.0</td>
</tr>
<tr>
<td>D.</td>
<td>-26.0</td>
<td>947.0</td>
<td>53.0</td>
</tr>
</tbody>
</table>

Figure 2. Diagram of a floor plan of the measurement site showing coordinate axes and four receiver anchors denoted by A, B, C and D

Figure 3. Experimental setup of dynamic target tracking in XY plane showing the train with tag and transmit antenna moving on rail road

VII. RESULTS

CRPF was implemented for dynamic target tracking using TDoA data from UWB tag and compared with EKF and HP. Results discussed in this paper are for 10 Monte Carlo runs and 800 particles. These values were chosen based on statistical analysis of CRPF performance. Figure 4 shows the comparison of the trajectories estimated by CRPF, EKF and HP with the true trajectory in XY plane.
It can be seen that the RMSE of EKF and HP is higher than CRPF. Table II shows that the RMSE for estimated trajectory of CRPF is 11.54 cm, EKF is 13.34 cm and HP is 19.57 cm. Thus, performance improvement in case of CRPF as compared to EKF and HP is 13.50% and 41.03% respectively. CRPF was found to outperform EKF and HP also for static positioning performed using the above described UWB localization platform [11].

VIII. CONCLUSION

In this paper, we compare the performance of a sequential Monte Carlo based filter called CRPF with EKF and HP for dynamic target tracking using the UWB localization platform. From the results of the research work, it can be seen that CRPF performs better than EKF and HP. CRPF is also very flexible in the sense that the cost function can be modified in a way which would be more appropriate for the specific application. Thus, it can be concluded that CRPF is a good choice whenever the system is non-linear and there is high uncertainty of the probabilistic model. From the analysis of all the results, it can be said that CRPF could be the state of art technology in position estimation problems as it offers various advantages such as ease of design and robustness with regard to the system’s probabilistic model.

REFERENCES


In order to evaluate the performance CRPF, RMSE error for all three algorithms was found by calculating the distance between the estimated and the true trajectory as shown in Figure 5.