Comparison of Extended and Unscented Kalman Filter for Localization of Passive UHF RFID Labels

<u>Theresa Nick¹</u>, Juergen Goetze¹, Werner John², and Gerhard Stoenner³

¹Information Processing Lab TU Dortmund University, Otto-Hahn-Str. 4, 44227 Dortmund, Germany, theresa.nick@tu-dortmund.de / juergen.goetze@tu-dortmund.de

² System Integration Laboratory, Dörener Weg 4b, 33100 Paderborn, Germany, werner.john@sysint-lab.eu
³ Deutsche Post AG, Hilpertstr. 31, 64295 Darmstadt, Germany, g.stoenner@deutschepost.de

Abstract

Due to the increased use of Radio Frequency Identification (RFID) in different fields of application it is reasonable to explore the benefit that can be obtained by the simultaneous localization of RFID tags. This paper describes the localization of a passive UHF RFID tag via Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) using the Received Signal Strength Indicator (RSSI) values. Simulation results based on measurements show that UKF achieves higher localization accuracies than EKF.

1 Introduction

Radio Frequency Identification (RFID) is becoming more and more popular and is used in logistics and other fields of application. But next to its ostensible purpose of identifying objects via their unique ID, it can also be employed in other areas. One of these applications is the simultaneous localization of tags such that readers know the object's position next to its identity.

The localization technique introduced in this paper is based on measured values and computer simulation. It should allow the localization using of-the-shelf equipment for reader, tags and antennae. The localization process only needs the Received Signal Strength Indicator (RSSI) values from the tag that should be localized. A use case for this localization via RFID is the localization of carts coming inside and moving outside of a mail distribution center of Deutsche Post AG. That way a database can always track which cart has been where at which point of time. This allows for missing carts to be found easier because possible actual locations can be narrowed down. It would lead to a reduction of the number of required carts which could highly reduce costs. The problem of the localization of the carts though is that there is not only one cart coming into the mail distribution center or leaving it, but that there are in most cases also carts parked on the side of the gates which send their ID back. Those carts should not be detected as coming in or leaving because they are stationary. Figure 1 shows such a scenario where a cart is just about ready to be moved out of the mail distribution center through the left gate and passing through the RFID localization area while many other carts are standing on both sides of that gate. In the front part of the picture it can be seen that there is also a cart which is passing by the RFID area inside the mail distribution center. It is important to be able to distinguish between these carts and the ones coming in or going out because in the database the status of the carts remaining inside the mail distribution center is not changed.



Figure 1: Test environment for RFID based trolley tracking

Using Received Signal Strength Indicator (RSSI) values for the localization of UHF RFID tags has been done in the past in various occasions and for different purposes [1–3]. Probably the best known system is the one called "LANDMARC" [4] which uses reference tags to locate an active RFID label in two dimensions with the help of RSSI values received from these reference tags and the label to be located. It has been extended to work with passive labels and in three dimensions in [5]. The present paper compares the use of different types of Kalman Filters for the localization of a moving or stationary passive UHF RFID tag. A variable number of reader antennae can be employed for the localization, but they are always at fixed positions. The RSSI values of all antennae are the only measurements taken for the localization process. The usage of Kalman Filter for RFID localization has been shown suitable in [6–9]. But compared to most of these publications in this paper the reader and its antennae are at fixed positions and only the label mounted to an object is moving.

2 Extended and Unscented Kalman Filter

This section illustrates the mathematics used for Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). For a more detailed explanation of those two algorithms see [10].

The Extended Kalman Filter is an extension of the Kalman Filter which can incorporate non-linearities in the prediction and measurement equations. Those are included through the use of Jacobian matrices. The input into the filter is a Gaussian position estimate of the previous time step t - 1 with mean μ_{t-1} and its covariance \mathbf{P}_{t-1} as well as the control u_t and the measurement z_t for updating the position. For the Extended Kalman Filter in a first step a prediction of the new mean $\bar{\mu}_t$ is calculated where the function g()is needed which represents the relation between the control of the present time step and the mean of the previous time step. Next is the calculation of a prediction of the new covariance $\bar{\mathbf{P}}_t$ where a Jacobian matrix of the control function and a covariance matrix of the process noise are used. With the help of this new covariance the Kalman Gain \mathbf{K}_t can be calculated with the Jacobian matrix of the measurement function and the covariance matrix of the measurement noise. Now the new values for the mean μ_t and covariance \mathbf{P}_t are computed wherefore the measurement prediction function is needed.

The Unscented Kalman Filter is also able to incorporate non-linearities in the filtering process. In contrast to the Extended Kalman Filter this is not done via the Taylor Expansion, but trough stochastic linearization. So-called Sigma Points are used which are located at the mean and symmetrically along the axis of the covariance with two points for each dimension. The Unscented Kalman Filter needs the same inputs as the Extended Kalman Filter. Its first step is to calculate the Sigma Points of the previous step. Next these points are propagated through a control function g and a predicted mean $\bar{\mu}_t$ and covariance $\bar{\mathbf{P}}_t$ are calculated. With the help of $\bar{\mu}_t$ and $\bar{\mathbf{P}}_t$ new Sigma Points $\bar{\chi}_t$ are calculated which now capture the uncertainty after the prediction step. For each of these Sigma Points a predicted observation point $\bar{\mathbf{Z}}_t$ is computed which is used to calculate the predicted observation \hat{z}_t and its uncertainty \mathbf{S}_t where the covariance of the additive measurement noise is included. For the calculation of the Kalman Gain \mathbf{K}_t the cross-covariance $\bar{\mathbf{P}}_t^{x,z}$ between state and observation is needed. Now the outputs μ_t and \mathbf{P}_t of the Unscented Kalman Filter can be computed which are the same output parameters as for the Extended Kalman Filter.

3 Simulation and Simulation Results

The Matlab simulation for the localization of UHF RFID labels can localize the tag in 3D. The considered space is $5m \times 5m \times 5m$ in which the antennae are placed and the tag is moving. In a first step a path is defined on which the tag is said to be moving. The RSSI values for all used antennae need to be calculated for the path. This is done based on an error model for the RSSI values which was established by measurements taken in our lab. For simulating realistic scenarios noise is added to these computed RSSI values to fit real world conditions where multi-path propagations and reflections occur. These noisy values are then used as

measurement inputs for the two different Kalman Filters. When needed in the measurement function the RSSI values are calculated backwards into distances $d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2}$ where x_i , y_i and z_i are the coordinates of the reader antenna i (i = 1, ..., l, l = number of antennae) and x, y and z are the coordinates of the label that has to be located. With the help of these distances d_i from each reader antenna to the tag the position of the RFID tag can be computed.

In the Kalman Filters not only the position of the label is predicted, but also its velocity. That is why the state vector \mathbf{x} has the following form in a three-dimensional localization simulation: $\mathbf{x} = \begin{bmatrix} x_p & y_p & z_p & v_x & v_y & v_z \end{bmatrix}^T$. The prediction function for the velocity at time step t is assumed to be the same as at the last time step: $\mathbf{v}_t = \mathbf{v}_{t-1}$. The prediction function for the position is based on the position of the last time step plus the time difference times the velocity.

The Extended and the Unscented Kalman Filter are used to localize a passive UHF RFID label in 3D. For the localization process the number of reader antennae is chosen between a minimum of three and a maximum of five. Three antennae are the minimum needed for a localization in three dimensions when only using RSSI values. The maximum of five is due to the fact that more reader antennae would mean more costs and hardly provide a further increase in localization accuracy. The results for the three-dimensional case are shown in Table 1 and Figure 2: The UKF outperforms the EKF in lower maximal error for different number of antennae as well as smaller overall error. For EKF and UKF it is visible that by changing the number of reader antennae from the minimum of three to four there is a huge decrease of the localization error. When further increasing the number of antennae the gain in localization accuracy is not that high.

Table 1:	Results	of	3D	localization	for	$\mathbf{E}\mathbf{K}\mathbf{F}$	and
UKF							

Number of Antennae	Error EKF	Error UKF
3	87.75cm	$38.58 \mathrm{cm}$
4	$74.75 \mathrm{cm}$	$27.77 \mathrm{cm}$
5	66.10cm	$23.28 \mathrm{cm}$



Figure 2: Results of 3D localization by UKF and EKF with 4 used antennae

It becomes visible in Figure 2 that the UKF performs better than the EKF. At the beginning both algorithms need some time steps to get to the correct path. These position estimates are not taken into account for the calculation of the localization error. After this starting period the UKF can track the original path of the RFID label closely while the EKF is not always that precise. The inferior simulation results of the EKF can be explained through the use of the Jacobian and how the noisy RSSI values influence the distances and therefore the estimation of the tag coordinates. Because the EKF takes only the derivative of the measurement equation into consideration some information of the correct tag position gets lost.

4 Conclusion And Future Work

It is shown in this paper that it is possible to localize a passive UHF RFID tag with the help of Extended or Unscented Kalman Filter using only the RSSI values collected at fixed reader antennae. The UKF clearly outperforms the EKF with a localization error of about 23cm when localizing the RFID tag in three dimensions. The Extended Kalman Filter reaches a localization accuracy of 66cm in the best case.

For the future it is desirable to verify the localization results with more real world data. Although we have real measured RSSI values further localization results may differ from the simulation outcomes. Due to multi-path propagation and reflection the error might increase and adjustments in the filters might be needed to better suite these real world conditions. To cut costs of the RFID localization system in a real world application it is attempted to reduce the number of reader antennae needed for the localization process. This could be done by incorporating other characteristics from the radio waves like traveling time from tag to antenna or maybe substitute antennae through other sensors. One possible substitution would be to use more than one label per cart, employ reference tags for the localization or a radar sensor. With more labels mounted to the cart more RSSI values are available and the geometric constraints between the tags can be used to improve the localization. The radar sensor would be especially useful for detection of a moving tag so that the reader does not have to be powered on all the time which would lead to a high amount of energy saving. It could as well give a first estimate of the location of the tag as well as its velocity. The reference tags could then provide further and detailed information about the label that has to be located via its RSSI values, for example. By the usage of reference tags also changes in the environment due to movement of objects would not be neglected because the RSSI values from the reference tags would be different as well as the RSSI values from the tag that is located. This way the localization result could be improved.

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