Camera-Assisted Localization of Passive RFID Labels

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***Abstract*—For indoor localization systems, Radio Frequency Identification (RFID) is an often chosen technique. A passive UHF RFID label can be localized via Received Signal Strength Indicator (RSSI) values using a Constrained Unscented Kalman Filter (CUKF). A camera-based localization technique which employs back projection method and movement estimation is combined with the RFID-based localization. This camera-assisted localization technique leads to an increase in localization accuracy by a factor of two compared to the Constrained Unscented Kalman Filter without camera assistance which already performes twice as good as the Unscented Kalman Filter (UKF).**

***Keywords*—RFID localization, camera-based localization, Constraint Unscented Kalman Filter, RSSI, back projection method**

I. Introduction

Due to the invention of Radio Frequency Identification (RFID), many new applications became possible, such as the automatic identification and tracking of goods in logistics, tracking of legal document copies or sport items and many more [1], [2]. Additionally to the main purpose of identifying objects, also the localization of items can be achieved simultaneously via this technique.

In this paper, a camera-assisted localization algorithm based on a Constrained Unscented Kalman Filter (CUKF) is developed which uses Received Signal Strength Indicator (RSSI) measurements from an unknown tag for RFID localization as well as the localization result of a camera-based localization method. This camera-based localization is done using a color histogram approach to detect the RFID-labeled object and a movement estimation to follow it in consecutive images to keep track of the object. The accuracy of the localization is improved due to the camera-based localization information because of its high location accuracy compared to the rather noisy RSSI measurements which are the basis for the RFID-based localization.

The scenario in which the camera-assisted localization algorithm is tested is the following: trolleys with yellow boxes which are labeled with an RFID tag are leaving or coming into a mail distribution center of Deutsche Post AG. This localization would allow for a tracking of the boxes (or trolleys) to prevent loss and to be able to connect different boxes with a trolley to the same tour taken by a truck. This connection would eliminate packaging errors where a trolley on a trip to a certain city is being stacked with boxes to a different destination. Because all of the mail distribution centers in Germany shall be equipped with the localization system, low-cost hardware is needed prohibiting the usage of custom designed readers, antennae or cameras. Therefore, only the RSSI values and the video sequence taken by an off-the-shelf camera are available as measurements and an intelligent algorithm needs to be able to achieve an accurate localization.

The paper is organized as follows: In Section II, previous work on the topic of localizing passive RFID labels based on RSSI readings is presented and the combination with a localization based on image processing is described. Section III depicts the localization algorithm which relies on an Unscented Kalman Filter and the camera-based localization approach. This is followed by a description of the simulation and its results, which are based on measured data, in Section IV. After that, Section V illustrates a demonstration tool which can perform a real-time localization based on the proposed method and is used to verify the simulation results. The paper finishes by giving a conclusion and an outlook on future work in Section VI.

II. Previous Work

Many different methods have been explored for the localization of active as well as passive RFID labels or the localization of readers due to fixed tags. A variety of parameters can be chosen to achieve a location estimate depending on the use case and the available hardware. [2]–[5] give a good overview over many of the systems and outline their different approaches. For the course of this paper, the focus is on the localization of passive RFID labels via RSSI measurements in combination with image processing.

In [6], [7], results of RSSI based localization of passive UHF RFID labels with the help of different Kalman Filters are presented. A Kalman Filter has been chosen because this type of filter has shown good results on RFID-based localization in the past [8]. However, as stated in [9] and [10], RSSI is not always reliable as a localization parameter due to changing environmental conditions leading to multipath propagation and reflections which will result in noisy RSSI measurements. Therefore, in [11] an environmental-adaptive RSSI based positioning algorithm is proposed which is used

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in [12] as an addition to the well-known system "LANDMARC" [13], where reference tags and a k-nearest neighbor (kNN) approach are applied to localize an active tag in two dimensions. The applicability of "LANDMARC" for passive tags and a three-dimensional localization has been shown in [14]. However, the localization is still only based on RSSI readings and might suffer from different effects influencing the electromagnetic wave and the resulting measurements. To overcome this problem other sensors can be incorporated into the localization process.

One possible sensor which can additionally be used for a localization is a camera. The combination of RFID-based and camera-based localization is shown to be working for a moving RFID reader and fixed tags in [15]–[17]. Isasi et al. [18] also use a combined RFID- and vision-based approach for fixed reader antennae and moving tags as it is done in this paper. Their focus though was the identification of persons and objects via RFID and the localization was only based on the camera image. This is contrary to this paper's approach where both methods are combined to achieve higher localization accuracy.

III. Localization Algorithm

This section is divided into four subsections: The first three contain the different basics for the proposed localization method. The last subsection shows how these different parts are combined.

A. Unscented Kalman Filter

The localization algorithm used for the camera-assisted localization of a passive UHF RFID label is based on an Unscented Kalman Filter (UKF) [19]. This type of Kalman Filter is able to incorporate non-linearities in the process and/or measurement function through stochastic linearization and is needed because the measurement function in this application is non-linear.

The input is a Gaussian location (x, y and z) and velocity estimate (v_x, v_y and v_z) of the previous time step $t-1$ with mean $\mathbf{x}_{t-1}$ and covariance $\mathbf{P}_{t-1}$. The necessary calculations of the Unscented Kalman Filter are shown in Table I in Eq. (1) to (12) and are explained as follows:

In the first step the Sigma Points of the previous time step are calculated where $\gamma = \sqrt{n+\delta}$ and $\delta = \alpha^2(n+\kappa)-n$ with α and κ as scaling parameters and n as the dimension of the state space which equals to six according to the three location and the three velocity estimates.

Next, these points are propagated through the control function g and a predicted mean $\bar{\mathbf{x}}_t$ and covariance $\bar{\mathbf{P}}_t$ are calculated where w_m and w_c are the weights according to

$$w_m^{[0]} = \frac{\delta}{n+\delta}$$
$$w_c^{[0]} = \frac{\delta}{n+\delta} + (1-\alpha^2+\beta) \text{ and}$$
$$w_m^{[i]} = w_c^{[i]} = \frac{1}{2(n+\delta)} \quad \text{for } i = 1,\ldots,2n$$

TABLE I
The Unscented Kalman Filter algorithm

$$\mathcal{X}_{t-1} = \left(\mathbf{x}_{t-1} \quad \mathbf{x}_{t-1}+\gamma\sqrt{\mathbf{P}_{t-1}} \quad \mathbf{x}_{t-1}-\gamma\sqrt{\mathbf{P}_{t-1}}\right) \tag{1}$$
$$\bar{\mathcal{X}}_t^* = g(\mathcal{X}_{t-1}) \tag{2}$$
$$\bar{\mathbf{x}}_t = \sum_{i=0}^{2n} w_m^{[i]}\, \bar{\mathcal{X}}_t^{*\,[i]} \tag{3}$$
$$\bar{\mathbf{P}}_t = \sum_{i=0}^{2n} w_c^{[i]} (\bar{\mathcal{X}}_t^{*\,[i]} - \bar{\mathbf{x}}_t)(\bar{\mathcal{X}}_t^{*\,[i]} - \bar{\mathbf{x}}_t)^T + \mathbf{R} \tag{4}$$
$$\bar{\mathcal{X}}_t = \left(\bar{\mathbf{x}}_t \quad \bar{\mathbf{x}}_t+\gamma\sqrt{\bar{\mathbf{P}}_t} \quad \bar{\mathbf{x}}_t-\gamma\sqrt{\bar{\mathbf{P}}_t}\right) \tag{5}$$
$$\bar{\mathbf{Z}}_t = h(\bar{\mathcal{X}}_t) \tag{6}$$
$$\hat{\mathbf{z}}_t = \sum_{i=0}^{2n} w_m^{[i]} \bar{\mathbf{Z}}_t^{[i]} \tag{7}$$
$$\mathbf{S}_t = \sum_{i=0}^{2n} w_c^{[i]} (\bar{\mathbf{Z}}_t^{[i]} - \hat{\mathbf{z}}_t)(\bar{\mathbf{Z}}_t^{[i]} - \hat{\mathbf{z}}_t)^T + \mathbf{Q} \tag{8}$$
$$\bar{\mathbf{P}}_t^{x,z} = \sum_{i=0}^{2n} w_c^{[i]} (\bar{\mathcal{X}}_t^{[i]} - \bar{\mathbf{x}}_t)(\bar{\mathbf{Z}}_t^{[i]} - \hat{\mathbf{z}}_t)^T \tag{9}$$
$$\mathbf{K}_t = \bar{\mathbf{P}}_t^{x,y} \mathbf{S}_t^{-1} \tag{10}$$
$$\mathbf{x}_t = \bar{\mathbf{x}}_t + \mathbf{K}_t(\mathbf{z}_t - \hat{\mathbf{z}}_t) \tag{11}$$
$$\mathbf{P}_t = \bar{\mathbf{P}}_t - \mathbf{K}_t \mathbf{S}_t \mathbf{K}_t^T \tag{12}$$

with β as a scaling parameter and $\mathbf{R}$ as the covariance matrix of the process noise.

With the help of $\bar{\mathbf{x}}_t$ and $\bar{\mathbf{P}}_t$, new Sigma Points $\bar{\mathcal{X}}_t$ are calculated, which now capture the uncertainty after the prediction step. For each of these Sigma Points, a predicted observation point is computed through the measurement function h. Now $\bar{\mathbf{Z}}_t$ is used to calculate the predicted observation $\hat{\mathbf{z}}_t$ and its uncertainty $\mathbf{S}_t$ where $\mathbf{Q}$ is the covariance of the additive measurement noise.

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. In a final step, the outputs $\mathbf{x}_t$ and $\mathbf{P}_t$ of the Unscented Kalman Filter can be computed with the help of the Kalman Gain $\mathbf{K}_t$ and the measurement $\mathbf{z}_t$.

B. Constrained Unscented Kalman Filter

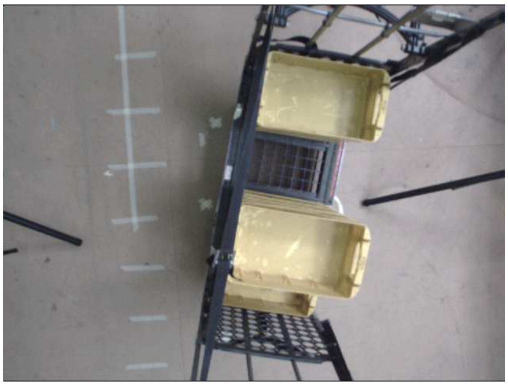
To incorporate different constraints into a Kalman Filter and convert it into a Constrained Unscented Kalman Filter (CUKF), various approaches are possible [20]. For the method proposed in this paper, two of those approaches are chosen: The first is a so-called "Perfect Measurement" which augments the measurement vector by components which are known and therefore have zero measurement noise. In this paper it is the height (y-coordinate in location estimate) of the RFID label which is always the same because the tag is fixed to a certain object (the yellow box), which is placed on a bigger object (the trolley). However, the missing measurement noise might lead to numerical problems. That is why it is transformed into a "Soft Constraint" which has to be approximately satisfied, i.e. a small nonzero measurement noise is assumed.

The second constraint is found with the help of the camera: only when an object is found in the present image, a localization result is available. This means on the contrary that if no camera-based localization result is obtained the object is not in the area which can be overseen by the camera. This leads to constraints for the width (x-coordinate of location estimate) and depth (z-coordinate) component of the location estimate. As described in [21], this constraint has to be checked at different stages of the UKF algorithm: First, it needs to be examined when the Sigma Points of the previous time step are calculated (as in Eq. (1)). The constraint has to be checked a second time after the Sigma Points are propagated through the process function (after Eq. (2)). A third examination is necessary after the estimation of the new location (see Eq. (11)) if the UKF violates the constraint.

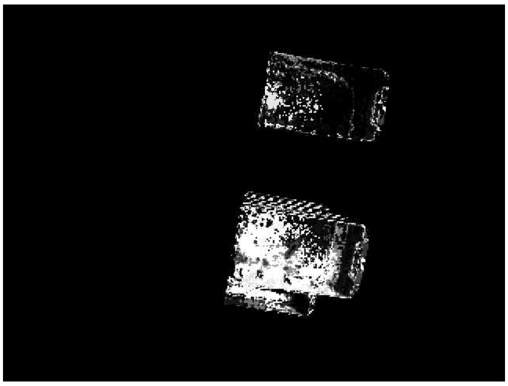
C. Camera-based localization

For the vision-based part of the localization method, an inexpensive off-the-shelf camera is used. Thus, the noise of the image is high and the image quality is poor which narrows down the number of algorithms which are usable for this localization. It has been decided to employ an algorithm based on a color histogram method analogue to parts of [22]. For this method, it is necessary to have sample data of the object which should be localized to train the algorithm. Based on this sample image, the color histogram of the object which shall be found is calculated. To calculate such a histogram, a so-called "Back Projection" is done. Back projection means that the image is converted into a grayscale image where every pixel of the image is chosen to belong to a certain group of the histogram based on its color scale value. In the back projection image, the pixel gets the dedicated grayscale value depending on the occurrence of this color in the picture. The range of the value is scaled between 0 and 255. The back projection image has a high probability of light image sections where the wanted object is to be found (see Fig. 1(b)). If morphological operations and thresholding are applied afterwards, smaller areas are merged to a continuous larger one and as a result of the thresholding a black and white picture is generated. In this picture, the connected areas are said to be relevant regions (see Fig. 1(c)). In these regions, a rectangle is placed and the center is said to be the desired location of the object. However, the procedure has the disadvantage that if the object contains to many colors, its histogram is not unique and the area on which the object is found might be too large. This is not the case here in our scenario because the boxes are unicolored.

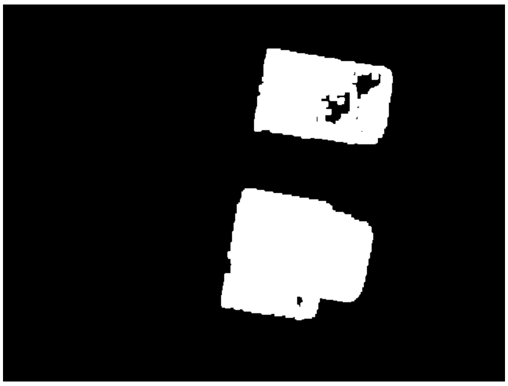
For the localization of the yellow box, it has to be kept in mind that it shall not only be localized once, but that its path should be tracked. Therefore, it is necessary to find the same yellow box in consecutive images. For that reason, once a box is detected, it is labeled with an identification number. To verify if the same box is found in the next image, a simple movement model is set up which assumes that the object is moving with a constant velocity. If an object is detected close



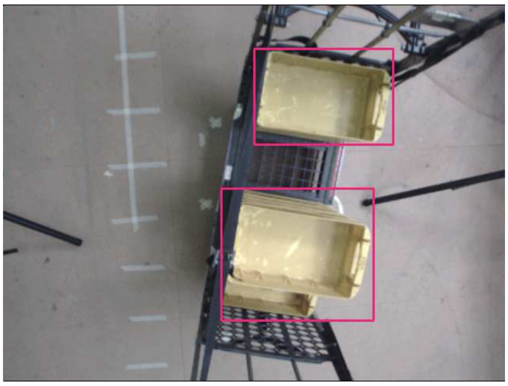
(a) Original image



(b) Grayscale image after back projection



(c) After morphological operations and thresholding



(d) Final image with found objects

Figure 1. Steps of back projection object detection

to the last location, it is said to be the same as the previous one and the ID is kept. However, if for example an object is leaving the image in the upper part and in the next picture a new object is appearing at the lower part of the image, it cannot be the same object and it will receive a new ID.

As can be seen in Fig. 1(d), the back projection method has the ability to find more than one object per image. This is of importance because a trolley can carry a couple of the tagged yellow boxes or more than one trolley with a box can be in the camera's image. With the proposed camera localization approach, it is therefore possible to distinguish between different RFID-labeled objects and a matching between RFID and camera localization can take place if needed.

It should be noticed that the camera is placed above the area where the localization will take place so that it cannot be obscured by other objects. Additionally, this rather simple algorithm for the object localization has been chosen because it does not depend on light conditions and a minimum of light can be secured because the localization is performed in an indoor scenario where employees need a certain amount of light to perform their work anyway. On top of that, only small changes in the lightning conditions are likely to happen if the gate of the distribution center is opened or closed.

D. Camera-Assisted RFID-Based Constrained Unscented Kalman Filter for localization

For the localization of the passive RFID label which is attached to a yellow box the state vector $\mathbf{x}$ of the Kalman Filter consists of the location in x-, y- and z-direction as well as the three velocities in each direction

$$\mathbf{x}\,(1:6) = [x \quad y \quad z \quad v_x \quad v_y \quad v_z]\,. \tag{13}$$

The process function g maps the movement of the tag from the previous time step to the present: the location of the actual time step is the location of the previous time step plus the velocity times the time difference between the two measurements Δt. The velocity is said to be the same leading to

$$g = [\mathbf{x}(1:3) + \mathbf{x}(4:6)\cdot\Delta t \quad \mathbf{x}(4:6)]\,. \tag{14}$$

Because of the height constraint, it is known that the y-coordinate is not changing and that the velocity in that direction is equal to zero. Additionally, g is a linear function so that a matrix vector multiplication is possible. Taking these two facts into account the process function g in Eq. (2) can be substituted by the matrix $\mathbf{F}$

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{15}$$

As described in Section III-B in the following steps of the Constrained Unscented Kalman Filter the compliance with the constraints due to an existing or non-existing camera-based localization estimate has to be checked.

A second check which needs to be done is the matching between RFID-based and camera-based localization. Because the camera area is in the middle of the area which is covered by the RFID antennae, a RFID-based localization result is available when the first camera localization takes place. Therefore, a simple matching between those two localizations results based on a distance threshold can be used. If the difference between the two location estimates is below a certain threshold, the camera-based location estimate is integrated into the RFID-based CUKF.

The next step of the localization is the measurement function h of the Unscented Kalman Filter which consists of the distance measurements $d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2}$ for $i = 1, \ldots, M$ (M equals the number of antennae) where x_i, y_i, z_i are the antennae positions and x, y, z the a priori estimates of the coordinates of the object which is localized. These distances are obtained from the measured RSSI values from the tag to each of the M antennae. As additional information (converting the UKF into a Constrained UKF), the difference between the known height of the tag (because it is fixed to the box which is placed on a trolley) and the estimated y-coordinate has to be zero. If existing, the difference of the location estimate of the camera-based localization and the x- and z-coordinates of the RFID-based localization should be zero as well. This leads to a measurement function h like

$$h = \begin{bmatrix} \sqrt{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2} \\ \vdots \\ \sqrt{(x_M - x)^2 + (y_M - y)^2 + (z_M - z)^2} \\ y - y_{height} \\ x - x_{cam} \\ z - z_{cam} \end{bmatrix} \tag{16}$$

where y_{height} is the known height at which the tag is positioned, x_{cam} and z_{cam} are the estimated locations in x- and z-direction from the camera-based localization.

The size of the measurement function might vary in the course of the simulation depending on the number of antennae from which RSSI measurements are available at the present time step and depending on the environmental conditions and the actual location of the tagged object because not all antennae will always get readings from the tag. Another factor influencing the size of the measurement function is whether a camera-based localization is available. The size of the measurement vector $\mathbf{z}_t$ also changes over time. It contains the measured distances d (calculated from the measured RSSI values), a zero for the difference between height y_{height} and measured y-coordinate and two zeros for the difference between camera-based localization result (x_{cam},z_{cam}) and the x- and z-coordinate. If no image-based localization is available these two zeros are omitted.

If the constraints were exactly kept, the covariance matrix of the measurement noise $\mathbf{Q}$ would contain zeros at the diagonal at these positions. But especially at the beginning of the localization process when the location is not yet estimated correctly this would lead to computational instabilities. Therefore, the constraints are softened meaning some deviation from this location is allowed leading to a nonzero element in the noise covariance matrix. These constraints can be hardened after some estimations when a good localization is already achieved. This approach makes sense for the y-coordinate using the height information, but is not reasonable for the camera-based localization because here the location of the center point of the object is calculated by the camera-based localization method. Therefore, the measurement noise in these components is the same during the complete estimation process.

IV. RESULTS

To test the performance of the proposed algorithm in a real world scenario, a test setup is build up consisting of an Intermec IF 61 Enterprise Reader, Joymax Electronics APX-026XNFR9 circular polarized patch antennae with 8.5bBic gain and the passive RFID tag Omni-ID Max Rigid Case for the RFID-based localization. The camera-based localization is done with a Playstation Eye camera from Sony Computer Entertainment.

Before the algorithm can be tested RSSI measurements at different distances are taken to find a relation between the RSSI values and the distance. This process can be repeated quite easily if the setup is transfered to a different place to take disturbances into account like multipath propagation or reflections and therefore adjust the formula between RSSI measurement and distance.

To now verify the algorithm, some test data is taken in this real world scenario and given to a Matlab simulation which computes the location based on the proposed camera-assisted Constrained Unscented Kalman Filter algorithm. The following parameters need to be set:

- Locations of antennae and correct tag location
- Initial state vector $\mathbf{x}_0$ and its covariance matrix $\mathbf{P}_0$
- The process noise covariance matrix $\mathbf{R}$
- The measurement noise covariance matrix $\mathbf{Q}$ for different scenarios (with or without camera-assistance).

The time difference Δt between the estimations can be extracted from the collected RSSI data because it has a time stamp included.

To be able to verify the error of the localization approach, the Root Mean Square Error (RMSE) of the location estimates is calculated as the difference between the estimated and the correct location as

$$RMSE = \sqrt{\frac{\sum_{t=1}^{k}(\hat{x}_t - x_t)^2 + (\hat{y}_t - y_t)^2 + (\hat{z}_t - z_t)^2}{k}} \tag{17}$$

where $\hat{x}_t$, $\hat{y}_t$, $\hat{z}_t$ are the estimated and x_t, y_t, z_t are the correct coordinates and k is the number of estimates.

A. Stationary test case

A first test case is to place the tagged object at a fixed location and take the RSSI measurements. The error is about 26cm for the proposed localization algorithm when RSSI readings from four antennae are available for the localization. This result of the Camera-Assisted Constrained UKF (CUKF_cam) can be compared to

- an Unscented Kalman Filter without camera-assistance (UKF) and
- a CUKF with the height of the tag as a constraint, but without the knowledge of the camera-based localization (CUKF_height).

The results of the various algorithms are shown in Table II for the stationary test case.

TABLE II
RESULTS OF 3D LOCALIZATION FOR STATIONARY TAG

Algorithm	UKF	CUKF_height	CUKF_cam
RMSE	136cm	60cm	26cm

It can be seen that the incorporation of the height constraint already decreases the localization error by roughly a factor 2 in comparison to the UKF and that the camera-assisted approach in combination with the height constraint is able to localize the object with higher accuracy compared to the methods without the camera assistance.

This higher accuracy of the camera-assisted localization can be explained by the additional information which is available through the image and the localization based on it. Particularly, it is not based on the properties of the electromagnetic wave like the RSSI measurements and therefore it is not subject to the same disturbances. This results in an excellent surplus to the RFID-based localization.

B. Moving test case

For a moving object, the tagged box on the trolley is driven once through the localization area on a straight line pushed by a person. Therefore, the velocity is not always the same as well as the line might not be completely straight. Hence, the error between the location estimate and the correct path can just be approximated, especially because the correct z-coordinate (depth) of the path is not known all of the time. Fig. 2 shows the results for the three dimensions separately, where approximately 140 estimates span a time of about 18 seconds. Only when the trolley with the yellow box is pushed through the range of the camera, the camera-assisted localization can take place. At the beginning and the end of the movement, the location estimation is done solely based on the RSSI measurements which is then equal to the information of the CUKF_height (which is shown in dotted lines in Fig. 2). For the z-component of the position estimate, a ground truth (dashed line) is only available in the camera area (based on the image).

Apparently, the location estimation is imprecise in the x-coordinate especially at the beginning of the localization process. However, the bad result at the beginning is not only due to the missing camera assistance and the initial value $\mathbf{x}_0$ of the filter: At the first estimates there is just the RSSI measurement of one RFID antenna on which the complete

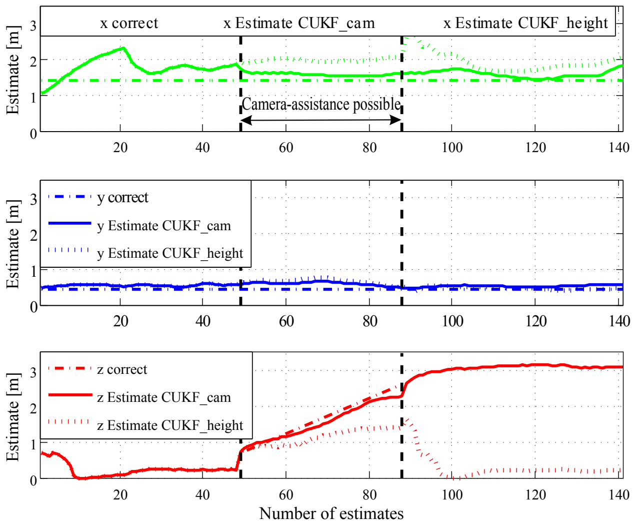


Figure 2. Simulation result for moving tag with partial camera-assisted localization separately for x-, y- and z-coordinate

localization is based. After RSSI measurements from a second antenna are available (after estimation 20), the positioning is less erroneous already. The results for CUKF_height (dotted line) and CUKF_cam (straight line) are the same in this area. In the course of the localization process, the location estimate is getting very precise particularly when a camera localization result is available and used for the localization (straight line). If the camera localization result is not used additionally to the RFID-based positioning, the error is still acceptable if the object is inside an area where many RSSI measurements are available (corresponds approximately to camera area). However, if the object moves out of this area, its location based on the CUKF_height is estimated quite badly especially regarding the z-coordinate, which is the depth component of the object. This is not the case when the camera localization result has been used in the camera area. Even when it is no longer available the localization based on the RSSI measurements is quite good because the starting point for this period of localization is better and because of the additional constraints from the missing camera-based localization. The overall error for this test case (inside the camera area) is about 75cm when the CUKF_height is used compared to a localization error of just around 36cm for the CUKF_cam.

V. Demonstrations

To accurately demonstrate the suitability of the proposed localization algorithm, a demonstration tool has been implemented to be able to test the approach in real world scenarios. It is possible to use different localization algorithms with or without camera-assistance. The program is able to convert the pixels at which an object is found into a location in x-, y- and z-coordinates if reference points are given to compute the relation between pixels and coordinates.

Fig. 3 and Fig. 4 show a screenshot of the demonstration tool and the camera image during the real time localization,

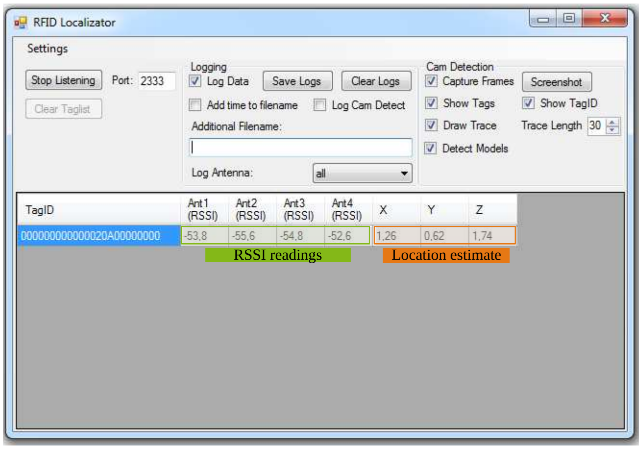


Figure 3. Screenshot of demonstration program

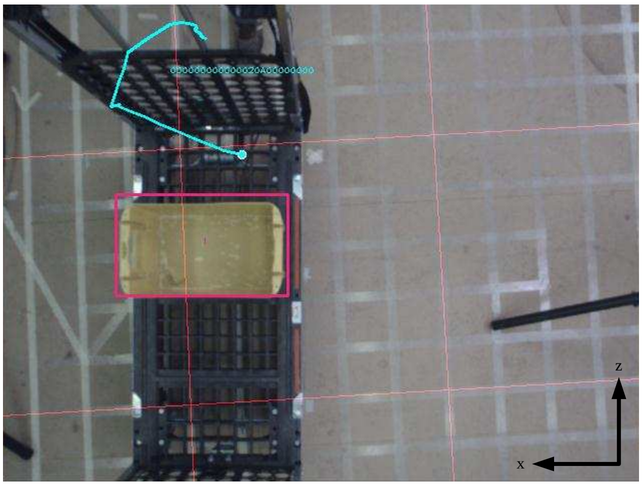


Figure 4. Screenshot of camera image with RFID-based and camera-based localization

respectively. In Fig. 3, the localization via RFID can be seen for one tag in x-, y- and z-coordinates as well as the actual measured RSSI values. Different settings are possible concerning the localization approach (which filter shall be used for the localization). The maximum number of antennae and their locations as well as the camera setting (white balance, gain, etc.) can also be changed.

Fig. 4 is a camera image where it can be seen that the path on which the tag (attached to the yellow box) has been estimated to be moving has some errors (blue line). This is due to the fact that for the estimation of this path only the UKF with height constraint (CUKF_height) has been used. It can be derived from the camera-based localization result (red rectangle around yellow box) that it would be advantageous to integrate this image information into the localization process as it is proposed in this paper to reduce the positioning error in this scenario.

This demonstration tool can be adapted easily if new localization algorithms shall be tested and it can be used for stationary as well as moving test cases. It is also possible to train the algorithm to find different objects in the camera image when a test image is given from which the back projection can be done and compared to the actual image.

VI. Conclusion and Future Work

In this paper, it is shown that the proposed Camera-Assisted Constrained Unscented Kalman Filter is able to localize a passive UHF RFID label accurately. Compared to an UKF and a CUKF without assistance from the camera, it achieves higher localization accuracy in different real world scenarios. The usage of a localization system solely based on the camera has the disadvantage of a very small coverage area and it would not be able to identify different objects of the same type as it can be done via RFID.

The camera-based localization is exemplarily done for the yellow boxes on a trolley in this paper. The procedure can easily be adjusted to find the trolleys in the image as well if an adequate model is built based on training data. Though, for the trolley it might not be enough information to use the back projection image, such that a different image processing algorithm might be needed for a precise localization or a marker has to be placed on it for localization purposes. However, even a rough estimate of the object's location could be helpful as additional information because only the height constraint is often not sufficient information for a good localization result.

At this point of time, the algorithm has only been shown to be able to follow one object in the camera image and it is automatically said to be the one which is tagged with an RFID label and from which RSSI measurements can be read just with the help of a simple matching technique. For future usage in a real use case, this method can be expanded to localize more objects via parallel employed filter. Then, a more advanced matching between the different RFID tags and detected objects from the image has to be carried out. Therefore, a distance measurement weighting between the RFID-based localization and the camera-based localization has to be implemented. Especially it needs to be considered that more boxes can be seen as one object in the camera image (as shown in Fig. 1(d)) and their IDs must all be assigned to the same object detected in the camera image.

A second aspect for future work can be the comparison of the CUKF to a particle filter which might be able to cope better with the noisy RSSI measurements. Its disadvantage though is the higher computational complexity depending on the number of particles used. A second disadvantage is that only one RSSI measurement at a time is used for an estimate or an additional trilateration approach has to be included. To avoid this a so-called Unscented Particle Filter can be incorporated which is a combination of Particle Filter and Unscented Kalman Filter.

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