Hybrid WSN-RFID Cooperative Positioning Based on Extended Kalman Filter

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***Abstract*—In this paper we propose a novel hybrid and cooperative positioning approach based on extended Kalman filter (EKF) to localize mobile targets in indoors. The algorithm fuses both received signal strength (RSS) measurements performed by nodes of a wireless sensor network (WSN) and proximity information from radio frequency identification (RFID) devices. Simulation results prove that the proposed cooperative approach outperforms the non-cooperative version of the algorithm.**

I. INTRODUCTION

Cooperative indoor localization is a research topic that has received great attention over the last years [1]. Many WSN-based localization approaches, for cost reasons, are based on RSS measurements as this type of measurement is simple to implement also in cheap devices. In addition, almost all communication standards provide a RSS indicator for each packet received by the radio chip.

Since the indoor environment is harsh from the radio frequency propagation point of view, the resulting RSS-based positioning accuracy is heavily affected. In order to improve the final performance, this paper extends the hybrid (WSN-RFID) localization approach presented in [2] by including the cooperative feature, which is the main novelty of this paper. In particular, the proposed algorithm supposes that unknown targets cooperate among them by exchanging positioning data. Moreover, an additional variance on WSN-based RSS measurements performed between unknown targets is introduced which takes into account the uncertainty deriving from the mobile position estimates.

The reminder of this paper is organized as follows. Section II introduces both positioning scenario and measurement models. Section III describes the hybrid-cooperative EKF algorithm. Simulation results are shown in section IV and, finally, section V concludes the paper.

II. SCENARIO DESCRIPTION

A. Localization Environment

We refer to a realistic positioning scenario depicted in Fig. 1 of size 50×50 m, where $A = 9$ fixed WSN anchors, $R = 8$ fixed RFID readers and $M = 4$ mobile targets are deployed. As it can be observed, WSN anchor nodes are placed according to a grid shape in order to maximize both positioning accuracy and availability, while the RFID readers are placed in each of the four main entrances and around the center of the environment.

The four mobile targets, which we want to localize and track, move along different trajectories represented by dotted lines in Fig. 1. Each mobile target is equipped with both a WSN node and a RFID tag. On one hand, the mobile target uses the WSN node to perform RSS measurements with respect to its WSN neighbors, which could be either fixed anchors or other mobile WSN targets (note that the WSN connectivity is calculated according to the communication radius, $R_{\text{WSN}} = 30$ m). On the other hand, the RFID tag attached to each mobile target is used to know whether the target is inside or outside the RFID readers' interrogation area modeled with a circle of radius $R_{\text{RFID}} = 6$m.

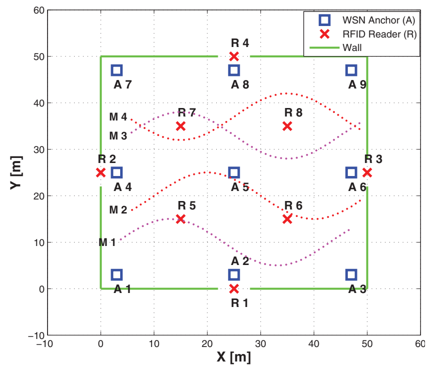

Figure 1. Hybrid WSN-RFID scenario.

B. Measurement Model

This section presents the adopted models for both WSN and RFID measurements.

1) WSN Measurements Modeling: We model RSS measurements by using the well known *log-normal shadowing path loss* model [3]. In particular, this model assumes that the received power $\tilde{P}$ (expressed in dBm) is a function of the distance between the transmitter and receiver (denoted with d) and corrupted by an additive Gaussian noise as follows:

$$\tilde{P}(d) = P_0 - 10\alpha \log_{10}(d/d_0) + X_\sigma. \quad (1)$$

where P_0 is the mean power received at the reference distance d_0 (typically 1 meter), α is the path loss exponent, which depends on the environment, and

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$X_\sigma \sim \mathcal{N}\left(0, \sigma_{\text{dB}}^2\right)$ is the noise contribution which models the shadowing effect. In order to apply this model, the channel model parameters $(\alpha, P_0, \sigma_{\text{dB}})$ should be known or estimated, for instance, by performing a preliminary experiment campaign as in [4].

2) RFID Measurements Modeling: Since RSS measurements provided by RFID are not reliable for positioning purposes, we use the RFID detection information as proximity data.

In order to integrate RFID measurements into the localization algorithm we use the distance based model presented in [2]. According to this model, when the mobile target is detected by a reader, the RFID target produces a constant distance measurement $\tilde{d}_T = R_{\text{RFID}}/2$ and it is assumed to be Gaussian distributed, $\tilde{d}_T \sim \mathcal{N}\left(R_{\text{RFID}}/2, \sigma_{\text{RFID}}^2\right)$ where $\sigma_{\text{RFID}}^2 = R_{\text{RFID}}^2/4$.

III. Hybrid Cooperative EKF Algorithm

A. Overview of EKF

Extended Kalman filter (EKF) provides an efficient recursive solution for non-linear discrete filtering problems with low complexity [5], and it is widely used in positioning and tracking applications.

Usually, a dynamic system can be modeled by using the following two discrete equations:

$$\mathbf{x}_k = f\left(\mathbf{x}_{k-1}, \mathbf{m}_{k-1}\right), \tag{2}$$
$$\mathbf{z}_k = h\left(\mathbf{x}_k, \mathbf{n}_k\right). \tag{3}$$

In particular, equation (2) represents the state transition equation, where $\mathbf{x}_k$ and $\mathbf{x}_{k-1}$ are the state vectors at the estimation time k and $k-1$, respectively. f is the state transition function, possibly nonlinear, and $\mathbf{m}_{k-1}$ is the process noise at time $k-1$ which is assumed to be Gaussian distributed, $\mathbf{m}_{k-1} \sim \mathcal{N}\left(0, \mathbf{Q}_{k-1}\right)$.

Equation (3) represents the observation equation, where $\mathbf{z}_k$ is the measurement vector at time k and h is the observation function which relates the measurements $\mathbf{z}_k$ with the state $\mathbf{x}_k$ at time k. Finally, $\mathbf{n}_k$ is the measurement noise which is assumed to be Gaussian distributed, $\mathbf{n}_k \sim \mathcal{N}\left(0, \mathbf{R}_k\right)$.

EKF is a kind of Bayesian filtering, which involves two stages namely '*prediction*' and '*correction*'. More in detail, the EKF first draws the *priori* estimate, denoted with $\hat{\mathbf{x}}_{k|k-1}$, and then corrects it to the *posteriori* estimate, denoted with $\hat{\mathbf{x}}_{k|k}$, by using the measurements $\mathbf{z}_k$.

The complete EKF procedure can be expressed by the following equations:

$$\hat{\mathbf{x}}_{k|k-1} = f\left(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{m}_{k-1}\right), \tag{4}$$

$$\mathbf{P}_{k|k-1} = \mathbf{A}_k \mathbf{P}_{k-1|k-1} \mathbf{A}_k^T + \mathbf{Q}_{k-1}. \tag{5}$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \left(\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k\right)^{-1}, \tag{6}$$

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - h\left(\hat{\mathbf{x}}_{k|k-1}, \mathbf{n}_k\right), \tag{7}$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k, \tag{8}$$

$$\mathbf{P}_{k|k} = \left(\boldsymbol{I}_n - \mathbf{K}_k \mathbf{H}_k\right) \mathbf{P}_{k|k-1}. \tag{9}$$

where $\mathbf{A}_k = \frac{\partial f}{\partial \mathbf{x}}\Big|_{\hat{\mathbf{x}}_{k-1|k-1}}$ is the Jacobian matrix of the transition function f evaluated around the previous *posteriori* state estimate, $\hat{\mathbf{x}}_{k-1|k-1}$, and $\mathbf{H}_k = \frac{\partial h}{\partial \mathbf{x}}\Big|_{\hat{\mathbf{x}}_{k|k-1}}$ is the Jacobian matrix of the observation function h evaluated around the *priori* state estimate, $\hat{\mathbf{x}}_{k|k-1}$.

Equations (4) and (5), are used in the *prediction phase*, in which the *priori* state state $\hat{\mathbf{x}}_{k|k-1}$ and the error covariance matrix $\mathbf{P}_{k|k-1}$ are estimated. After that, equations from (6) to (9), are used in the *correction phase*, during which the *posteriori* state $\hat{\mathbf{x}}_{k|k}$ and the error covariance matrix $\mathbf{P}_{k|k}$ are updated by using the optimal Kalman gain $\mathbf{K}_k$ and the innovation vector $\tilde{\mathbf{y}}_k$.

B. Hybrid-cooperative EKF

The design of the proposed algorithm, named hybrid-cooperative EKF (hcEKF), can be subdivided into three parts: state modeling, hybridization and cooperation.

1) State Modeling: Since the final positioning accuracy and complexity strongly depend on the modeling of the system dynamics, a suitable state model is important to be chosen. In this work, we applied the PV (Position-Velocity) model [6] which is often used in scenarios with mobility.

The PV model supposes that the target moves with constant velocity within the interval $\triangle t_k$ between two consecutive time steps k and $k-1$. The corresponding state vector is composed of both position and velocity components, $\mathbf{x}_k = [\boldsymbol{p}_k, \boldsymbol{v}_k]^T$, where $\boldsymbol{p}_k = [x_k, y_k]$ and $\boldsymbol{v}_k = [\dot{x}_k, \dot{y}_k]$ are position and velocity vectors, respectively, represented in the 2D Cartesian coordinate system (the extension to the 3D case is straightforward).

According to the PV model, the state transition function f is a linear function of the state:

$$\mathbf{x}_k = f\left(\mathbf{x}_{k-1}, \mathbf{m}_{k-1}\right) = \mathbf{x}_{k-1} + \boldsymbol{v}_{k-1} \cdot \triangle t_k + \mathbf{m}_{k-1}, \tag{10}$$

In this case, the process noise $\mathbf{m}_{k-1}$ models the unknown random accelerations that affect the target maneuvers. The acceleration components are modeled with zero mean and variances $[\sigma_{\ddot{x}}^2, \sigma_{\ddot{y}}^2]$, uncorrelated with time. Consequently, the covariance matrix $\mathbf{Q}_{k-1}$ can be expressed as:

$$\mathbf{Q}_{k-1} = \begin{bmatrix} \triangle t_k^2 \mathbf{I}_2 \\ \triangle t_k \mathbf{I}_2 \end{bmatrix} \operatorname{diag}\left(\sigma_{\ddot{x}}^2, \sigma_{\ddot{y}}^2\right) \begin{bmatrix} \triangle t_k^2 \mathbf{I}_2 \\ \triangle t_k \mathbf{I}_2 \end{bmatrix}^T. \tag{11}$$

where $\mathbf{I}_2$ is a 2×2 identity matrix and $\operatorname{diag}(\sigma_{\ddot{x}}^2, \sigma_{\ddot{y}}^2)$ is a 2×2 diagonal matrix.

2) Hybridization: This section presents the hybridization part which consists in fusing the measurements from WSN and RFID. We denote with $\mathcal{A} = \{1, 2, \ldots A\}$, $\mathcal{M} = \{1, 2, \ldots M\}$ and $\mathcal{R} = \{1, 2, \ldots R\}$ the sets of fixed WSN anchors, WSN mobiles and fixed RFID readers, respectively, deployed in the environment. Moreover, we denote with $\mathcal{A}_k^m \subseteq \mathcal{A}$, $\mathcal{M}_k^m \subseteq \mathcal{M}$ and $\mathcal{R}_k^m \subseteq \mathcal{R}$ the sets of WSN anchors, WSN mobiles and RFID readers, respectively, connected to a generic mobile node m at time k.

Given the mobile node $m \in \mathcal{M}$, its hybrid observation vector can be written as:

$$\mathbf{z}_k^m = \left[\tilde{\mathbf{P}}_{\mathcal{A}_k^m} \; \tilde{\mathbf{P}}_{\mathcal{M}_k^m} \; \tilde{\mathbf{d}}_{\mathcal{R}_k^m}\right]^T, \tag{12}$$

where $\tilde{\mathbf{P}}_{\mathcal{A}_k^m}$ and $\tilde{\mathbf{P}}_{\mathcal{M}_k^m}$ are the sets of RSS measurements performed by the mobile node m w.r.t the connected WSN anchors and WSN mobile nodes, respectively, while $\tilde{\mathbf{d}}_{\mathcal{R}_k^m}$ is the set of RFID-based distances (i.e. RFID proximity information).

The observation function related to the mobile node m can be written as follows:

$$h\left(\mathbf{x}_k^m\right) = \begin{bmatrix} \mathbf{h}_k^{\mathcal{A}_k^m}\left(\mathbf{x}_k^m\right) \\ \mathbf{h}_k^{\mathcal{M}_k^m}\left(\mathbf{x}_k^m\right) \\ \mathbf{h}_k^{\mathcal{R}_k^m}\left(\mathbf{x}_k^m\right) \end{bmatrix}. \tag{13}$$

where $\mathbf{h}_k^{\mathcal{A}_k^m}\left(\mathbf{x}_k^m\right)$, $\mathbf{h}_k^{\mathcal{M}_k^m}\left(\mathbf{x}_k^m\right)$, $\mathbf{h}_k^{\mathcal{R}_k^m}\left(\mathbf{x}_k^m\right)$ are the observation functions which refer to the sets of connected WSN anchors, WSN mobiles and RFID readers, respectively, at time k.

Let $\boldsymbol{p}_k^i$, $i \in \mathcal{A}_k^m$, be the position coordinates of the WSN anchor i connected to the mobile node m at time k. The corresponding observation function related to a generic connected WSN anchor node i is given by:

$$h_k^{m,i} = P_0 - 10\alpha \log_{10}\left(\text{dist}\left(\boldsymbol{p}_k^m, \boldsymbol{p}_k^i\right)/d_0\right) + X_\sigma, \tag{14}$$

where $\text{dist}(\boldsymbol{p}_k^m, \boldsymbol{p}_k^i)$ is the Euclidean distance between the current position of the mobile node m and the connected anchor node i, calculated as:

$$\text{dist}\left(\boldsymbol{p}_k^m, \boldsymbol{p}_k^i\right) = \sqrt{(x_k^m - x_k^i)^2 + (y_k^m - y_k^i)^2}, \tag{15}$$

The corresponding contribution to the global Jacobian matrix $\mathbf{H}_k^m$ is obtained by partially differentiating (14) around the *priori* state estimate $\hat{\mathbf{x}}_{k|k-1}^m$:

$$\mathbf{H}_k^{m,i} = \frac{-10\alpha\left(\hat{\boldsymbol{p}}_{k|k-1}^m - \boldsymbol{p}_k^i\right)}{\ln(10)\,\text{dist}^2\left(\hat{\boldsymbol{p}}_{k|k-1}^m, \boldsymbol{p}_k^i\right)}. \tag{16}$$

Note that $\mathbf{H}_k^{m,i}$ is a vector row composed of two elements which refer to the position components while the speed components are zero because these are independent from the measurements.

Similarly, let $\boldsymbol{p}_k^j$, $j \in \mathcal{M}_k^m$, be the position coordinates of the WSN mobile j connected to the mobile node m at time k. The corresponding observation function related to a generic connected WSN mobile node j is:

$$h_k^{m,j} = P_0 - 10\alpha \log_{10}\left(\text{dist}\left(\boldsymbol{p}_k^m, \boldsymbol{p}_k^j\right)/d_0\right) + X_\sigma, \tag{17}$$

It is worth observing that $\boldsymbol{p}_k^j$ is the position of a mobile neighbor which is not perfectly known. In fact, node m can receive the current position estimate from node j. Therefore, similar to (16), the corresponding contribution to $\mathbf{H}_k^m$ can be expressed as:

$$\mathbf{H}_k^{m,j} = \frac{-10\alpha\left(\hat{\boldsymbol{p}}_{k|k-1}^m - \hat{\boldsymbol{p}}_{k-1|k-1}^j\right)}{\ln(10)\,\text{dist}^2\left(\hat{\boldsymbol{p}}_{k|k-1}^m, \hat{\boldsymbol{p}}_{k-1|k-1}^j\right)}. \tag{18}$$

where $\hat{\boldsymbol{p}}_{k-1|k-1}^j$ is the *posteriori* position estimate broadcast by the node j at time $k-1$. Since $\hat{\boldsymbol{p}}_{k-1|k-1}^j$ is affected by error, its contribution can be compensated by increasing the corresponding RSS uncertainty in the $\mathbf{R}_k^m$ matrix as explained in the next subsection.

Finally, let $\boldsymbol{p}_k^l$, $l \in \mathcal{R}_k^m$, be the position coordinates of the RFID reader l connected to the mobile node m at time k. Since the RFID-based proximity information is translated into a distance (see section II-B2), the corresponding observation function is given by the Euclidean distance:

$$h_k^{m,l} = \text{dist}\left(\boldsymbol{p}_k^m, \boldsymbol{p}_k^l\right) + n_{\text{RFID}}, \tag{19}$$

The corresponding contribution to the global Jacobian matrix $\mathbf{H}_k^m$ is obtained by partially differentiating (19) around the *priori* state estimate $\hat{\mathbf{x}}_{k|k-1}^m$:

$$\mathbf{H}_k^{m,l} = \frac{\hat{\boldsymbol{p}}_{k|k-1}^m - \boldsymbol{p}_k^l}{\text{dist}\left(\hat{\boldsymbol{p}}_{k|k-1}^m, \boldsymbol{p}_k^l\right)}. \tag{20}$$

Note that in the above equations, the subscript k used in $\boldsymbol{p}_k^i$ and $\boldsymbol{p}_k^l$ can be omitted as both WSN anchors and RFID readers have fixed positions.

3) Cooperation: The proposed algorithm adopts a cooperative approach. In fact, unknown mobile targets cooperate among them in order to improve their final position accuracy. It is worth noting from (12) that the unknown mobile target m uses not only information from the fixed nodes (i.e. both WSN anchors and RFID readers whose positions are perfectly known) but also RSS measurements from the neighboring unknown mobile targets, $\tilde{\mathbf{P}}_{\mathcal{M}_k^m}$. Since the positions of the mobile neighbors are not perfectly known, the target m uses their position estimates sent over the air, (see (18)), which of course are affected by their position uncertainties. Therefore, in order to properly take as input these positioning data, the target node m, apart from the intrinsic uncertainty on the RSS measurements σ_{dB}^2, should take into account also additional uncertainties due to these neighbors' position estimates.

Let $e_{d,k}^{mj}$ be the distance error between nodes m and j deriving only from the position error of node j, denoted with $e_{p,k}^j$. We assume that $|e_{d,k}^{mj}| \approx |e_{p,k}^j|$ and $e_{d,k}^{mj}$ is Gaussian distributed with zero mean and whose variance can be upper bounded by using the state covariance matrix $\mathbf{P}_{k|k}^j$ provided by the EKF running on node j:

$$\text{Var}\left(e_{d,k}^{mj}\right) \approx \text{Var}\left(|e_{p,k}^j|\right) \leq \text{tr}\left(\mathcal{P}_{k|k}^j\right), \tag{21}$$

where $\mathcal{P}_{k|k}^j$ is the sub matrix of $\mathbf{P}_{k|k}^j$ which refers only to the position components.

Taking into account the distance error of the mobile target j introduced in (18), the RSS model can be rewritten as:

$$\begin{aligned} \tilde{P}_k^{mj} &= P_0 - 10\alpha \log_{10}\left(\frac{\hat{d}_k^{mj} + e_{d,k}^{mj}}{d_0}\right) + X_\sigma \\ &= P_0 - 10\alpha \log_{10}\left(\hat{d}_k^{mj}/d_0\right) + X_\sigma + X_{\sigma,k}^{mj}, \end{aligned} \tag{22}$$

where $\hat{d}_k^{mj}$ is the Euclidean distance calculated between the current *posteriori* estimated positions of nodes m

and j and $X_{\sigma,k}^{mj} = -10\alpha\log_{10}(1 + e_{d,k}^{mj}/\hat{d}_k^{mj})$ is the additional RSS noise contribution.

We denote with $\mathcal{X}_{\sigma,k}^{mj} = X_\sigma + X_{\sigma,k}^{mj}$ the new additive noise on the RSS measurement w.r.t. the mobile node j. The final objective is to calculate the variance of $\mathcal{X}_{\sigma,k}^{mj}$, needed as input to the covariance matrix $\mathbf{R}_k^m$ of the observation vector. Since the variance calculation of $\mathcal{X}_{\sigma,k}^{mj}$ is not an easy task, we use the following approximation $\log_{10}(1+x) \approx x$ valid around $x = 0$ (i.e. for small values of $|e_{d,k}^{mj}/\hat{d}_k^{mj}|$). Consequently, $\mathcal{X}_{\sigma,k}^{mj} \approx X_\sigma - 10\alpha e_{d,k}^{mj}/\hat{d}_k^{mj}$.

From the above approximation and assumptions, we have that $E(\mathcal{X}_{\sigma,k}^{mj}) = 0$, therefore, the variance of $\mathcal{X}_{\sigma,k}^{mj}$ can be calculated as:

$$\begin{aligned}\sigma^2_{\mathcal{X}_{\sigma,k}^{mj}} &= E({\mathcal{X}_{\sigma,k}^{mj}}^2) \approx \sigma^2_{\mathrm{dB}} + 100\alpha^2 \mathrm{Var}(e_{d,k}^{mj})/{\hat{d}_k^{mj}}^2 \\ &\leq \sigma^2_{\mathrm{dB}} + 100\alpha^2 \mathrm{tr}(\mathcal{P}_{k|k}^j)/{\hat{d}_k^{mj}}^2. \qquad (23)\end{aligned}$$

Finally, the measurement noise covariance matrix for mobile m is given by:

$$\mathbf{R}_k^m = \mathrm{diag}(\underbrace{\dots \sigma^2_{\mathrm{dB},i} \dots}_{i\in\mathcal{A}_k^m} \; \underbrace{\dots \sigma^2_{\mathcal{X}_{\sigma,k}^{mj}} \dots}_{j\in\mathcal{M}_k^m} \; \underbrace{\dots \sigma^2_{\mathrm{RFID},l} \dots}_{l\in\mathcal{R}_k^m}). \qquad (24)$$

The designed hcEKF procedure is reported in pseudo code form in Alg. 1.

Algorithm 1 Hybrid-cooperative EKF (hcEKF)

Require: hybrid measurements from WSN and RFID $\left\{\mathbf{z}_k^m = \left[\tilde{\mathbf{P}}_{\mathcal{A}_k^m}\ \tilde{\mathbf{P}}_{\mathcal{M}_k^m}\ \tilde{\mathbf{d}}_{\mathcal{R}_k^m}\right]^T\right\}_{m=1}^M, \forall k \in [1, K]$
Initialization
  set $k = 0$ and initial state $\left\{\hat{\mathbf{x}}_{0|0}^m, \mathbf{P}_{0|0}^m\right\}_{m=1}^M$
for k =1 **to** K **do** {time slot index}
  for m =1 **to** M **do** {mobile index}
    calculate noise covariance $\mathbf{R}_k^m$ using (24)
    predict $\hat{\mathbf{x}}_{k|k-1}^m$ and $\mathbf{P}_{k|k-1}^m$
    compute $\tilde{\mathbf{y}}_k^m$ and $\mathbf{K}_k^m$
    update state $\hat{\mathbf{x}}_{k|k}^m$ using (8)
    update the covariance matrix $\mathbf{P}_{k|k}^m$ using (9)
    communicate $\hat{\mathbf{p}}_{k|k}^m$, and $\mathrm{tr}(\mathcal{P}_{k|k}^m)$ to neighbors
  end for
end for

IV. Simulation Results

During simulations, we used the log-normal model parameters extrapolated from a real experiment [4], where $P_0 = -49$ dBm, $d_0 = 1$ m, $\alpha = 3$, $\sigma_{\mathrm{dB}} = 6$ dB. In total we tested four different versions of the EKF algorithm, namely hybrid-cooperative EKF (hcEKF), cooperative EKF (cEKF) based only on WSN, hybrid EKF (hEKF) without cooperations and a simple EKF (EKF) based only on WSN without cooperation. The positioning accuracy, evaluated after 100 Monte Carlo simulation runs, is displayed in Fig. 2 in terms of cumulative distribution functions of the localization error.

As it can be observed, the proposed hcEKF algorithm, which includes both cooperation and RFID hybridization, outperforms the other three ones. In addition, we can observe that the cEKF is slightly better than hEKF. Thus, we can conclude that the proposed cooperation approach based only on WSN provides an improvement larger than the contribution provided by the hybridization only. Finally, the RFID hybridization algorithm (hEKF) without cooperation outperforms the simple EKF using only WSN measurements without cooperation, which confirms the results reported in [2].

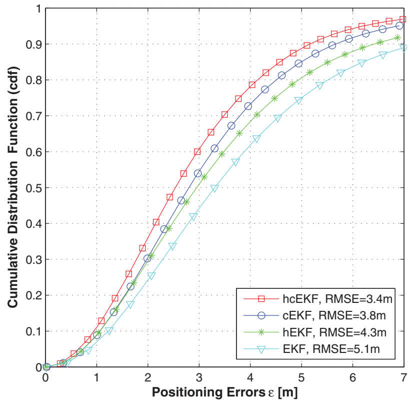

Figure 2. Positioning performance.

V. Conclusions and Future Works

This paper presented an application of the EKF to the tracking problem in indoors. The proposed solution adopts the hybridization of measurements from both WSN and RFID devices. Moreover, it uses the cooperation among mobile targets to improve the final positioning accuracy. In fact, the designed hcEKF algorithm takes into account the position estimates from mobile nodes and their uncertainties. Simulation results show that the proposed algorithm outperforms the non cooperative one. Future work will include the validation of the simulation results through prototyping and real-life testing.

Acknowledgment

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