Multi-agent tracking in wireless sensor networks: model and algorithm

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Abstract: In this work an algorithm to track multiple agents in an indoor Wireless Sensor Actor Network is proposed. The algorithm falls into the category of the radio frequency localization/tracking methods, since it exploits the strength of the wireless communications among nodes to establish the position of a set of mobile nodes within a network of fixed nodes placed in known locations. In this sense, a radio channel model is introduced that allows to estimate the distances among nodes to attain localization and tracking (range-based approach). Moreover, to compensate for the scant robustness of power measurements, the loss effects induced by wireless communication, the intrinsic uncertainty of unstructured environments, the algorithm resorts to an Extended Kalman Filter to process the node measurements and reach a desired level of tracking performance. Finally, the design phase is validated through the implementation and the experiments on a real testbed.

Key–Words: wireless sensor network, localization, tracking, Kalman filter

1 Introduction

In recent years, the employment of Wireless Sensor Actor Networks (WSANs) for gathering data from the environment have been increasingly envisaged for building management systems and environment control [1][2], thanks to their versatility of use, easiness of deployment, pervasiveness of data, adaptability to system/environment variations [3]. Examples in this sense are given by Heating and Ventilation Air Conditioning systems [4] employing more and more advanced control techniques (e.g. [5]) that would benefit from a detailed mapping of the internal building parameters; by event detection and surveillance systems, where the heterogeneity of agent devices and the computational grid created by the network itself allow the definition of data fusion policies [6]; by localization and tracking systems where the wireless devices can exploit the received power signal during broadcast/peer-to-peer communication to perform position estimation [7].

The work presented in this paper belongs to this last framework, the Radio Frequency (RF) based localization and tracking, and in particular to the multi-agent tracking problem, where a set of mobile devices are moving within a network of fixed (and known) position similar devices (beacons), with which they communicate through a RF channel exchanging information on the surrounding.

State of the art In the framework of distributed systems composed of not-expensive embedded devices, one immediate advantage of RF-based tracking with respect to other methodologies is that the former does not need additional hardware components such as ultrasound, infrared, or light modules, to generate the localization signal that is then measured to compute the angle of arrival, the time of arrival, or time difference of arrival [8].

Differently, the RF-based method parasitically exploits the communication flow that is anyway ongoing among the nodes, and the measurement techniques is relying on the Radio Signal Strength (RSS) either basically inverting the relation between the distance and the received power (radio-channel model), or matching the received power with a pre-compiled map of the environment linking power values to positions. Common references for the former range-based methods and the latter range-free methods are respectively [9] and [10].

In this context, it appears how the accuracy in the localization/tracking strongly depends on the quality of the specific embedded hardware devices and how the algorithmic solutions aim at providing software correction procedure to improve the basic performance of the system.

In particular, a solution is sought that, while guaranteeing a certain level of tracking accuracy, is

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easy to implement, does not require high resources to the embedded device, is robust to node failure, and quick enough to converge for real-time use.

This work is coupled with a companion paper [11], where the implementation of the multi-agent tracking system is discussed. The motivation of this choice resides in the fact that, beyond the adopted models and the algorithmic solutions developed, in the framework of embedded device applications, also the specific implementation plays a crucial rôle in reaching the desired (and designed) performance.

Paper organization Sec. 2 introduces the channel model adopted by the tracking algorithm, while in Sec. 3 we describe our proposed algorithm for determining mobile nodes positions through an Extended Kalman Filter (EKF) [12] approach. Sec. 4 and Sec. 5 contain, respectively, a simulation based on experimental network data and some conclusions.

In general, we will use bold fonts to indicate vectorial quantities, plain italic fonts to indicate scalar ones, capital vertical fonts to indicate matrices.

2 Channel modeling

The performances of tracking algorithms are influenced by the effects of noises and disturbances introduced into the communication channel, so it is necessary to identify these contributions as accurately as possible. The measurements of received power exchanged by agents in a Wireless Sensor Actor Network (WSAN) are affected by objects in the environment (such as walls or furnitures) that cause attenuation, reflection, diffraction and diffusion effects. Moreover, errors that vary over time are caused by generic noises and interferences. Based on these considerations, we present a general channel model which takes into account different kind of disturbances. Then we focus on a reduced channel model, subject to particular assumptions, that we employ to design the multi-agent tracking algorithm.

2.1 General model

As we previously stated, to model the channel in an indoor environment it is necessary to consider different factors: The free-space path loss, which expresses the power loss due to dissipation of energy in the channel, the fading phenomena, like shadowing and multi-path, which express the variability of the channel.

A WSAN is usually treated as a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where the set $\mathcal{N}$ of the nodes (i.e. agents) communicate along the edges (i.e. communication links) specified by the set $\mathcal{E}$. Given a node i, the set $\mathcal{V}(i) := \{j \mid (i,j) \in \mathcal{E}, i \neq j\}$ collects its neighbors.

In our context the WSAN is primarily composed of a set $\mathcal{F}$ of F nodes in fixed positions, that do not know a priori their neighbors $\mathcal{V}(i)$, $i = 1, \dots, F$, but instead they know their positions $\boldsymbol{z}_i := (\overline{x}_i, \overline{y}_i)$, in the 2D space.

A well agreed channel model is the log-distance path loss model [13], where the received power is linked to the transmission power through a log-normal model of path loss, and other contribution terms are added to take into account of the other disturbing effects. The model that describes the wireless channel between two nodes, in terms of received power P_{ij}, is the following [14]:

$$\begin{aligned} P_{ij} &:= P_j^{tx} + r_j + f_{pl}(d_{ij}) + f_{sf}(\boldsymbol{z}_i, \boldsymbol{z}_j) \\ &\quad + f_a(\boldsymbol{z}_i, \boldsymbol{z}_j) + v_{ff}(t) + o_i, \end{aligned} \tag{1}$$

where i and j are the receiver and transmitter node, at a distance $d_{ij} := \|\boldsymbol{z}_i - \boldsymbol{z}_j\|$ ($\|\cdot\|$ being the classical euclidean norm). Moreover, P_j^{tx} is the transmitted power, r_j is the transmission offset between the nominal and the effectively transmitted power (which is usually reported in the datasheet of the devices); $f_{pl}(\cdot)$ represents the path loss; $f_a(\cdot)$ represents the channel asymmetry factor; $f_{sf}(\cdot)$ models the slow fading components while the $v_{ff}(\cdot)$ represents the fast ones, and $o_i(\cdot)$ represents the measured received strength offset of the receiving node.

2.2 Simplified model

The parameters of the Eqn. (1) depend on the environment where the WSAN is deployed and the specific hardware of the wireless devices. In general, to perform a channel parameter identification, the model of Eqn. (1) is simplified assuming that the transmission power of the sensors is set at the maximum level (i.e. $P_j^{tx} = 0$ dBm, $\forall j \in \mathcal{N}$) so that the transmitter offset is almost zero, $r_j \cong 0$ dBm. Furthermore, we consider that $o_i = 0$, $\forall i \in \mathcal{N}$, since the offsets can be easily compensated exploiting a distributed strategy [14] [1]. Lastly, the fast fading effect $v_{ff}(t)$ is removed, by averaging the received power over a set of $0 < C_{ij} \leq C$ consecutive measures: $\overline{P}_{ij} := \sum_{k=1}^{C_{ij}} P_{ij}^k$. It follows that the

[1]Experimental evidence indicates that agent offsets o_i are not negligible and can be substantially large for some nodes (up to 6 dBm). The effect of this offset is to bias the estimate of the distance between two nodes, which is particularly harmful in tracking applications.

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average received power $\overline{P}_{ij}$ becomes:

$$\overline{P}_{ij} = \beta - 10\gamma \log_{10}(d_{ij}) + f_{sf}(\boldsymbol{z}_i, \boldsymbol{z}_j) + f_a(\boldsymbol{z}_i, \boldsymbol{z}_j). \quad (2)$$

Since the components of slow fading and channel asymmetry are independent Gaussian random variables of variance σ_{sf}^2 and σ_a^2 respectively, they can be combined into one zero-mean random variable q_{ij} with variance equal to $\sigma^2 = \sigma_a^2 + \sigma_{sf}^2$:

$$\overline{P}_{ij} = \beta - 10\gamma \log_{10}(d_{ij}) + q_{ij}. \quad (3)$$

From Eqn. (3) it is clear that β and γ are the only parameters that determine the model of the communication channel. Being the components of slow fading and channel asymmetry independent Gaussian random variables, we can use a (distributed) least-squares estimator to estimate those parameters, as it has been addressed in [13].

3 Tracking algorithm

Suppose that in the WSAN a set $\mathcal{M}$ of M mobile nodes can freely move. Thus the WSAN is overall constituted by $F + M$ agents, in the set $\mathcal{N} = \mathcal{F} \oplus \mathcal{M}$. The proposed algorithm, that allows to estimate the 2D position of a mobile node is based on the assumptions that, at each time step k, $k \in \mathbb{Z}$ each mobile node m, $m \in \mathcal{M}$, knows:

- the coordinates $\boldsymbol{z}_n$ of each fixed node $n \in \mathcal{F}$;
- the power P_{mn} received from each $n \in \mathcal{V}_k(m)$, fixed node over a period of time $[(k-1) \quad k]$, where $\mathcal{V}_k(m)$ is the set of the F_k neighbors of node m in the period $[(k-1) \quad k]$ (notice that $F_k \leq \dim(\mathcal{F})$ changes at each time step k);
- the channel parameters β and γ;

Aim of the algorithm is the disjoint estimation of the coordinates $\boldsymbol{\xi}_m(k) := (x_m(k), y_m(k)) \in \mathbb{R}^2$ of the mobile nodes, at each time step k.

3.1 State-space model

Define the quantities

$$\mathrm{Z}(k) := \begin{bmatrix} \boldsymbol{z}_{n_1} \\ \vdots \\ \boldsymbol{z}_{n_{F_k}} \end{bmatrix} \in \mathbb{R}^{F_k \times 2}$$

$$h_{n_i}(\boldsymbol{\xi}_m(k), \boldsymbol{z}_{n_i}) := \beta - 10\gamma \log_{10}(\|\boldsymbol{\xi}_m(k) - \boldsymbol{z}_{n_i}\|) \in \mathbb{R}$$

$$\mathbf{h}(\boldsymbol{\xi}_m(k), \mathrm{Z}(k)) := \begin{bmatrix} h_{n_1}(\boldsymbol{\xi}_m(k), \boldsymbol{z}_{n_1}) \\ \vdots \\ h_{n_{F_k}}\left(\boldsymbol{\xi}_m(k), \boldsymbol{z}_{n_{F_k}}\right) \end{bmatrix} \in \mathbb{R}^{F_k}$$

and

$$\boldsymbol{\psi}(k) := \begin{bmatrix} \overline{P}_{mn_1}(k) \\ \vdots \\ \overline{P}_{mn_{F_k}}(k) \end{bmatrix} \in \mathbb{R}^{F_k}$$

For each mobile node m we have the state model:

$$\boldsymbol{\xi}_m(k+1) = \mathrm{A}\,\boldsymbol{\xi}_m(k) + \mathbf{w}(k) = \boldsymbol{\xi}_m(k) + \mathbf{w}(k) \quad (4)$$

and the measurements model:

$$\boldsymbol{\psi}(k) = \mathbf{h}(\boldsymbol{\xi}_m(k), \mathrm{Z}(k)) + \mathbf{v}(k) \quad (5)$$

where $\mathrm{Z}(k)$ is the matrix of known positions $\boldsymbol{z}_{n_i}$, with $i = 1, \ldots, F_k$ of the fixed nodes and $\boldsymbol{\xi}_m(k)$ is the state of the system, i.e. the 2D position of each mobile node $m \in \mathcal{M}$; $\boldsymbol{\psi}(k)$ is the output of the system, made of F_k powers stored by the mobile node and available at the time k. The process noise $\mathbf{w}(k)$ and the measurement noise $\mathbf{v}(k)$ are white, with zero mean and variance $\mathrm{W} \in \mathbb{R}^{2\times 2}$ and $\mathrm{V}(k) \in \mathbb{R}^{F_k \times F_k}$, respectively. $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are uncorrelated.

As we can see, the state transition model is linear and the matrix A is the identity matrices, denoting a typical behavior of a simple random walk. Thus the mobile node is represented as a point mass moving on the 2D plane, surrounded by a cloud of Gaussian uncertainty. The model of the measures is rather constituted by the channel model (3), which is non-linear. Notice how the measurement model is time variant, i.e. its dimension varies at each time step k according to the number F_k of the collected power measurements. Specifically, at each time step k a mobile node m collects F_k averaged measurements $\overline{P}_{mn_i}(k)$ from its dynamic neighbors $n_i \in \mathcal{V}_k(m)$.

3.2 Structure of the algorithm

Assume without loss of generality that $\dim(\mathcal{M}) = 1$. We define $\boldsymbol{\xi}(k) := \boldsymbol{\xi}_m(k)$ to indicate the position of the only mobile node $m \in \mathcal{M}$. The idea behind the algorithm is to operate two different types of filtering depending on the number F_k. If $F_k < 3$ the mobile node updates its state following an open-loop approach, otherwise it uses an EKF technique.

The choice of two approaches derives from the fact that we want to provide the EKF a minimum number of measures to update the estimate $\widehat{\boldsymbol{\xi}}(k|k)$. That minimum has been arbitrarily set equal to 3, recalling somewhat the constraint that appears in the algorithms based on trilateration/triangulation methods. If the measures available in the various sampling instants are less than 3, the algorithm expects to leave the filter in a open loop. The

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mobile node continues to regard as an estimate of the current position the last estimated position based on measurements received, but increasing step by step the variance of the filtering error. This approach forces the filter to consider the mobile node still in the same position both if there is packet loss (or the mobile node is simply in a dead zone) and if the acquired measurements are somehow corrupted.

Now let's see in detail the two types of filtering presented. Every period $[(k-1) \;\; k]$ the mobile node m identifies the set $\mathcal{V}_k(m)$, i.e. the F_k neighboring nodes, based on the measurements that it has collected in that time interval. If $F_k \geq 3$ the function $\mathbf{h}(\cdot)$ is linearized near the point $\widehat{\boldsymbol{\xi}}(k|k-1)$, which is the best estimation of the mobile node state at the instant k. Then the Jacobian:

$$\mathrm{H}(k) = \left[\frac{d\mathbf{h}(\boldsymbol{\xi},\cdot)}{d\boldsymbol{\xi}}\right]\Bigg|_{\boldsymbol{\xi}=\widehat{\boldsymbol{\xi}}} \in \mathbb{R}^{F_k\times 2}$$

is computed, which yields

$$\mathrm{H}(k) = -\frac{10\gamma\log_{10}\mathrm{e}}{\left\|\widehat{\boldsymbol{\xi}}(k|k-1)-\mathrm{Z}(k)\right\|^2}\left(\widehat{\boldsymbol{\xi}}(k|k-1)-\mathrm{Z}(k)\right)$$

Then, the minimum variance linear estimator $\widehat{\boldsymbol{\xi}}(k|k)$ of the state $\boldsymbol{\xi}(k)$, based on the observations $\boldsymbol{\psi}(k)$, is computed through the recursive algorithm:

$$\begin{aligned}
\Lambda(k) &= \mathrm{H}(k)\,\mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T + \mathrm{V}(k)\\
\mathrm{L}(k) &= \mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T\,\Lambda(t)^{-1}\\
\mathrm{Q}(k|k) &= \mathrm{Q}(k|k-1) - \mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T\,\Lambda^{-1}\,\mathrm{H}(k)\,\mathrm{Q}(k|k-1)
\end{aligned}$$

where the minimum variance linear predictor $\widehat{\boldsymbol{\xi}}(k+1|k)$ is given by

$$\begin{aligned}
\widehat{\boldsymbol{\xi}}(k+1|k) &= \mathrm{A}\widehat{\boldsymbol{\xi}}(k|k) = \widehat{\boldsymbol{\xi}}(k|k)\\
\mathrm{Q}(k+1|k) &= \mathrm{A}\,\mathrm{Q}(k|k-1)\,\mathrm{A}^T + \mathrm{W} = \mathrm{Q}(k|k) + \mathrm{W}
\end{aligned}$$

with $\Lambda(k)$ variance of the innovation process $\mathbf{e}(k) = \boldsymbol{\psi}(k) - \mathrm{H}(k)\widehat{\boldsymbol{\xi}}(k|k-1)$ and $L(k)$ gain of the filter.

If $F_k < 3$ we have:

$$\begin{aligned}
\widehat{\boldsymbol{\xi}}(k|k) &= \widehat{\boldsymbol{\xi}}(k|k-1) & \widehat{\boldsymbol{\xi}}(k+1|k) &= \widehat{\boldsymbol{\xi}}(k|k)\\
\mathrm{Q}(k|k) &= \mathrm{Q}(k|k-1) & \mathrm{Q}(k+1|k) &= \mathrm{Q}(k|k) + \mathrm{W}
\end{aligned}$$

that jointly become:

$$\begin{aligned}
\widehat{\xi}(k+1|k) &= \widehat{\xi}(k|k-1)\\
\mathrm{Q}(k+1|k) &= \mathrm{Q}(k|k-1) + \mathrm{W}
\end{aligned}$$

outlining clearly the effect of the stationary solution. The scheme of the algorithm is summarized by Alg. 1. The use of the EKF approach lies on the fact that it is easy to implement and it does not require significant computational resources, thanks to the structure of the filter itself and to the size of the system.

Algorithm 1 Generic mobile node tracking

$\widehat{\boldsymbol{\xi}}(k|k) \in \mathbb{R}^2$; $\mathrm{Q}(k|k) \in \mathbb{R}^{2\times 2}$ and $k = 0, 2, \ldots$

$\sigma_w \in \mathbb{R}$, noise model variance

$\sigma_v \in \mathbb{R}$, noise measure variance

set: $\widehat{\boldsymbol{\xi}}(0|-1) = \boldsymbol{\mu}_0$
$\mathrm{Q}(0|-1) = \mathrm{Q}_0$
$\mathrm{W} = \sigma_w^2\mathrm{I}_2$

set up of the measurements data set, collecting F_k power transmission from neighboring nodes.

for $k = 0, 2, \ldots$ **do**
  $\mathrm{V}(k) = \sigma_v^2 I_{F_k}$
  if $F_k \geq 3$ **then**
    $\Lambda(k) = \mathrm{H}(k)\,\mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T + \mathrm{V}(k)$
    $\mathrm{L}(k) = \mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T\,\Lambda(t)^{-1}$
    $\widehat{\boldsymbol{\xi}}(k|k) = \widehat{\boldsymbol{\xi}}(k|k-1) + \mathrm{L}(k)\left[\boldsymbol{\psi}(k) - \mathbf{h}\left(\widehat{\boldsymbol{\xi}}(k|k-1)\right)\right]$
    $\mathrm{Q}(k|k) = \mathrm{Q}(k|k-1)$
    $= \mathrm{Q}(k|k-1)\,\mathrm{H}(k)^T\,\Lambda^{-1}\,\mathrm{H}(k)\,\mathrm{Q}(k|k-1)$
  else
    $\widehat{\boldsymbol{\xi}}(k|k) = \widehat{\boldsymbol{\xi}}(k|k-1)$
    $\mathrm{Q}(k|k) = \mathrm{Q}(k|k-1)$
  $\widehat{\boldsymbol{\xi}}(k+1|k) = \widehat{\boldsymbol{\xi}}(k|k)$
  $\mathrm{Q}(k+1|k) = \mathrm{Q}(k|k) + \mathrm{W}$

Initial conditions The initial conditions of the algorithm are defined as $\widehat{\boldsymbol{\xi}}(0|-1) = \boldsymbol{\mu}_0$ $\mathrm{Q}(0|-1) = \mathrm{Q}_0$, with $\boldsymbol{\mu}_0 = \mathbb{E}[\boldsymbol{\xi}(0)]$ and $\mathrm{Q}_0 = \mathrm{var}\{\boldsymbol{\xi}(0)\}$. Since these quantities are not known in advance, specific estimation techniques can be used to get a guess. Trilateration, bounding box or least-square methods are some of the simplest and most popular for estimating the initial position [15].

Standard deviation σ_w of model noise $\mathbf{w}(k)$ Typically, to tune the EKF statistical procedures are used, as the cumulative periodogram test of Bartlett. For this specific case, however, we opted for an empirical calibration. Assuming that the mobile node is anchored to a human user, its variance, at each $[(k-1) \;\; k]$, can be set equal to that associated to a typical human motion, and therefore to define the diagonal elements of W. If we considered the fastest man in the world, with a sampling time of 60 ms between two consecutive estimations, the variance model would correspond to 0.3844 m^2, which can be thought as an upper bound to the variance.

Standard deviation σ_v of measurement noise $\mathbf{v}(k)$ This variance is usually easily available from the specific of sensing device with whom measurements are performed. Since, in this case, the measuring instrument is the communication channel, all the variances of the fading effects and asymmetry of the

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channel should be accurately evaluated. In Sec. 4 a practical example for a specific device is given.

4 Simulations with experimental setup

To validate the algorithm described in Sec. 3 some simulation have been performed on the base of the network data derived from the WSAN installed in the Department of Information Engineering (DEI) of the University of Padova [3]; the testbed considered (a portion of the mentioned WSAN) comprises 12 TMOTE™ SKY [16], ultra low power IEEE 802.15.4 compliant wireless devices, whose Chipcon CC2420 radio has an accuracy of 6 dBm. Here, the agents have a distance of about 4 meters from each other on a almost regular triangular grid of 15×10 m^2.

For the estimation of the channel parameters β, γ of (3) the least-square method in [13] which is a distributed version of [14] has been adopted. The results ($\gamma = 2.04$, $\beta = -41.69$ dBm) provides the model in Fig. 1 with a variance $\sigma^2 = 7.57$ m^2. The packet loss probability in Fig. 1, equal for each agent, is obtained as a least-square interpolation of experimental data collected in the testbed of DEI.

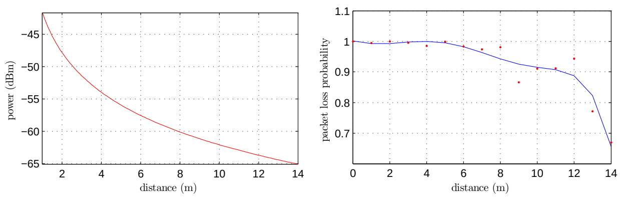

Figure 1: Left: power model $P = \beta - \gamma \log_{10} d$, as function of distance d. Right: packet loss probability. The red dots are samples computed on experimental data; the blue line is their least-square interpolation.

The movement of an agent is simulated through a random walk model

$$\boldsymbol{\xi}(k+1) = \begin{bmatrix} 1 & 0.1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0.1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \boldsymbol{\xi}(k) + \mathbf{w}(k)$$

$$\boldsymbol{\psi}(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \boldsymbol{\xi}(k) + \mathbf{v}(k)$$

where $\xi_1(0) \sim \mathcal{U}[0, 15]$, $\xi_2(0) \sim \mathcal{U}[0, 10]$ and the variances of model and measure noise $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are respectively given by:

$$Q = 9.4 \begin{bmatrix} 0.01 & 0.1 & 0 & 0 \\ 0.1 & 1 & 0 & 0 \\ 0 & 0 & 0.01 & 0.1 \\ 0 & 0 & 0.1 & 1 \end{bmatrix} \quad R = 0.0315 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

4.1 Performance evaluation

In general, the performances of any tracking algorithm depend on different factors, such as density and connectivity of the beacons, computation and communication costs, fault tolerance and robustness. In Fig. 2, the position estimation error $||\widehat{\boldsymbol{\xi}} - \boldsymbol{\xi}||_2$ is plotted for different algorithm parameters, as a criteria to evaluate the goodness of the tracking algorithm. Interestingly, the value of C (maximum number of

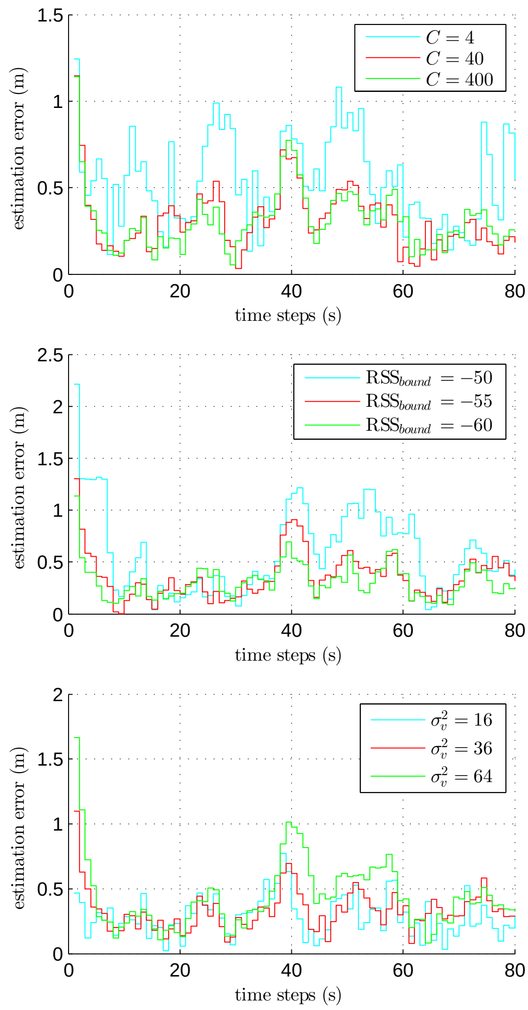

Figure 2: Estimation errors for different simulation parameters.

RSS data that each agent collects from neighbors to average the received power), over a certain threshold, does not affect significantly the position estimate, while the promptness of the system slows down increasing C. The system behaves similarly as for the bound on the received power, and increasing RSS_{bound} (the minimum power level acceptable for node-to-node distance estimation) would lower the number of useful signals in the localization process. Finally, increasing the measurement noise variance

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σ_v^2, worsen the performance, as expected.

If the extended version of the Kalman filter has become necessary to deal with the non linearity of the system, the use of an Unscented Kalman Filter (UKF) or a Sequential Monte Carlo (SMC) method has not be considered since these two approaches are proven to not improve significantly the performance in terms of localization accuracy. In fact, the SMC, which is in general a better solution than a UKF [17], tends to outperform the Kalman as the localization errors increase and it cannot considerably filter the non-Gaussian components.

5 Conclusions

In this work, an algorithm for multi-agent tracking in wireless networks is presented, employing a RF-channel model to estimate the distance among nodes. Moreover, to mitigate the nuisances induced by the not perfect wireless communication, by the implementation in an unknown and unstructured environment, and by the presence of noisy measurements, an EKF is employed to provide corrected estimates of the mobile agent positions. The simulations with data coming from an experimental testbed validate the goodness of the approach and assess it is suitable for a real time implementation on embedded devices.

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