INTERVAL-BASED LOCALIZATION USING SENSORS MOBILITY AND FINGERPRINTS IN DECENTRALIZED SENSOR NETWORKS

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ABSTRACT

This paper is focused on the decentralized localization problem of mobile sensors in wireless sensor networks. Based on a combined localization technique, it uses accelerometer, gyroscope and fingerprinting information to solve the positioning issue. Using the sensors mobility, the proposed method computes first estimates of sensors positions. It then proceeds to a decentralized localization scheme, where the network is divided to different zones. RSSIs fingerprints are jointly used with mobility information in order to compute position estimates. Final position estimates are obtained by means of interval analysis where all uncertainties are considered throughout the estimation process.

Index Terms— Fingerprints, interval analysis, localization, mobility, wireless sensor networks

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are networks composed of small devices, having sensing, computing and communication units [1]. In almost all applications of WSNs, knowing the sensors positions is a key issue, since all sensed data are tightly related to the geographical locations where measurements are made. Different approaches have been proposed for sensors localization. These approaches are mainly anchor-based methods, in which some sensors, called anchors, have known positions and the others, called nodes, need to be localized by exchanging information with anchors.

Among anchor-based localization methods, some are based on the Received Signal Strength Indicator (RSSI) [2], performing distance estimation or connectivity detection. While distance estimation techniques convert the RSSIs to distances using the channel pathloss model [3], connectivity-based methods compare RSSIs to power thresholds, leading to more robust computations. Other RSSI-anchor-based methods collect scenario information [4], commonly known as fingerprinting information. Here characteristics, like contour, colors, RSSI and many others, are gathered to model the state of the environment. In our previous work [5], we proposed a centralized localization algorithm using fingerprints, computations being performed in a central unit.

This paper proposes a decentralized localization technique using fingerprinting and mobility information. Being a decentralized approach, it consists of dividing the whole area into different zones, having each a central calculator. A configuration phase is first needed, before starting the localization process, to collect RSSIs at different positions in each zone. A mobile node collects then RSSIs from anchors at each time step, and sends them to the calculators neighboring it, where local position estimations are computed using the Weighted K-Nearest Neighbors (WKNN) [6]. Local estimates are then combined leading to a global one. Moreover, nodes are equipped with accelerometers and gyroscopes [7], yielding their accelerations and orientations respectively. These information are used with a third-order mobility model to compute another position estimate for each node. Both estimates are finally combined using interval analysis [8], leading to boxes including the real positions of the mobile nodes. The novelty of this method compared to [5] remains in its decentralized nature, in using gyroscope and in considering a third-order mobility model.

This paper is organized as follows. Section II introduces the localization methodology. Section III illustrates the combination algorithm with interval analysis technique. In Section IV, simulation results and comparison experiments are discussed whereas Section V concludes this paper.

2. DESCRIPTION OF THE METHODOLOGY

The proposed method is an anchor-based decentralized technique for localization in a D-dimensions surveillance area, with $D = 2$ or 3 for a two-dimensional or a three-dimensional area respectively. This kind of method considers two types of sensors: anchors and nodes. The anchors are fixed beforehand with known positions, denoted by $\boldsymbol{a}_i = (a_{i,1}, ..., a_{i,D})\,, i \in \{1, ..., N_a\}$. In contrary, the nodes are fixed or mobile with unknown positions, denoted by $\boldsymbol{x}_j(t) = (x_{j,1}(t), ..., x_{j,D}(t))\,, j \in \{1, ...N_x\}$. In order to localize the nodes in a decentralized manner, the surveillance area is divided into N_Z zones, set according to the unregulated configuration of the area or else equally [9], as shown in Figure 1. Each zone is equipped with a zone center calculator for gathering and computing the zone's information. Calculators, denoted by $\boldsymbol{c}_z = (c_{z,1}, ..., c_{z,D})\,, z \in \{1, ..., N_Z\}$, could be small computers or sensors of the network with more complex computation and storage capabilities.

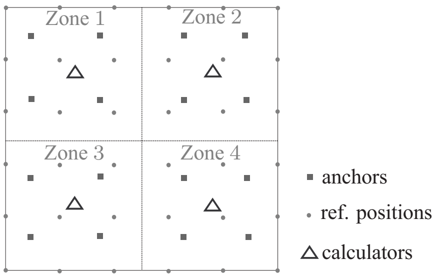

Fig. 1. Repartition of anchors, reference positions and calculators in the surveillance area.

Now that the physical entities of the network are defined, let us consider the mobility issue of the nodes. Indeed, one could track nodes' trajectories by equipping them with accelerometers. However, these devices yield instantaneous nodes' accelerations in their coordinate systems. Being able to rotate and to have accelerations in the Global Coordinate System (GCS) of the surveillance area, nodes are also equipped with gyroscope [7]. These devices yield the orientation of the nodes with respect to the GCS. Measurements of both devices are then combined, leading to nodes accelerations in the GCS. These quantities are then used, with a third-order mobility model, to compute first position estimates of the nodes.

Second estimates could be obtained by using fingerprinting information. To this end, the anchors broadcast signals over the network, with the same initial powers. Signals powers decrease with the increase of their traveled distances, which means that a given position within the surveillance area would be characterized theoretically by a unique set of Received Signal Strength Indicators (RSSIs), each from an anchor, and this according to its distances to the anchors. One is then able to model the network with RSSI-fingerprints, associating RSSIs to positions in the network [4]. To this end, and having a decentralized network with N_Z zones, $N_{p.z}$ reference positions are uniformly generated in each zone z, $z \in \{1, ..., N_Z\}$. These positions are denoted by $\boldsymbol{p}_{n.z} = (p_{n,1.z}, ..., p_{n,D.z})$, where $n \in \{1, ..., N_{p.z}\}$. Figure 1 shows an example of a repartition of anchors, calculators and reference positions over the surveillance area. By putting a sensor consecutively at the reference positions, one could measure the RSSIs of all anchors signals at these positions. Let $\xi_{p_{n,i.z}}$ be the power of the signal emitted by the anchor i and received at the reference position $\boldsymbol{p}_{n.z}$ of the zone z. These RSSIs are set in a vector given by

$$\boldsymbol{\xi}_{\boldsymbol{p}_{n.z}} = \left(\xi_{p_{n,1.z}}, ..., \xi_{p_{n,N_a.z}}\right), z \in \{1, ..., N_Z\}.$$

This leads to N_Z databases, the z-th one having $N_{p.z}$ couples $\left(\boldsymbol{p}_{n.z}, \boldsymbol{\xi}_{\boldsymbol{p}_{n.z}}\right)$, where $n \in \{1, ..., N_{p.z}\}$ and $z \in \{1, ..., N_Z\}$. The databases are stored in their corresponding calculators, to be used in the following for localization. Once the fingerprinting databases are configured, nodes travel in the surveillance area and collect RSSI information. Their RSSI vectors would be used with the databases to compute local estimates by the calculators. Local estimates are then combined together, then with the first mobility estimates leading to more accurate ones.

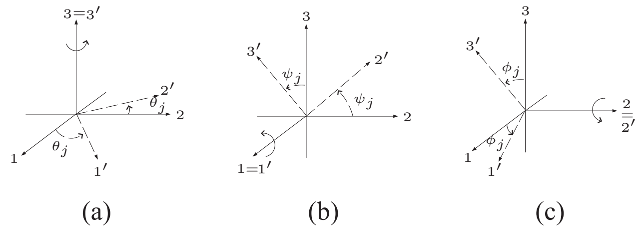

Fig. 2. Illustration of rotations in three-dimension space($D = 3$).

3. INTERVAL-BASED ALGORITHM

The interval analysis [8] provides an outer approximation of the solution of an inequality problem. Applied to nodes positioning in wireless sensor networks, solutions would be D-dimensional boxes including the real solution of the problem, D being the dimension of the surveillance area. In the following, it will be shown how the incertitude over accelerations, orientations and RSSI measurements could be considered to solve the localization problem.

3.1. Mobility estimates

Each node j is equipped with an accelerometer and a gyroscope, as discussed previously. Let $\gamma'_j(t)$ be the instantaneous acceleration vector of the node j at time t, given by its accelerometer according to the Node's Coordinate System (NCS). When a certain rotation occurs to a node in a real scenario, its NCS will be modified from the Global Coordinate System (GCS), and $\gamma'_j(t)$ will not be anymore in the GCS, and thus using it to compute the absolute coordinates of the node in the GCS will not be accurate. Consequently, at each time t, a node j measures as well its orientation angles using its gyroscope. Considering the case of a three-dimensions space ($D = 3$), the gyroscope of a node j at time t yields three angles denoted by $\theta_j(t)$, $\psi_j(t)$ and $\phi_j(t)$. These angles represent respectively the single rotation angles of the NCS with respect to the GCS around the 3rd coordinate axis, the 1st one and the second one, and this counterclockwise. See Figure 2 for illustration, where 1, 2 and 3 denote the axes of the GCS and 1', 2' and 3' denote the axes of the NCS. Let $\boldsymbol{\gamma}_j(t)$ be the nodes absolute 3D acceleration vector according to the GCS. Then

$$\boldsymbol{\gamma}_j(t) = \Re\left(\theta_j(t), \psi_j(t), \phi_j(t)\right) \boldsymbol{\gamma}'_j(t), \qquad (1)$$

where the first column of the 3D rotation matrix $\mathfrak{R}$ is given by

$$\begin{pmatrix} \cos\theta_j \cos\phi_j \\ \cos\theta_j \sin\psi_j \sin\phi_j + \sin\theta_j \cos\psi_j \\ -\cos\theta_j \cos\psi_j \sin\phi_j + \sin\theta_j \sin\psi_j \end{pmatrix},$$

and its second and third ones are defined respectively by

$$\begin{pmatrix} -\sin\theta_j \cos\phi_j \\ -\sin\theta_j \sin\psi_j \sin\phi_j + \cos\theta_j \cos\psi_j \\ \sin\theta_j \cos\psi_j \sin\phi_j + \cos\theta_j \sin\psi_j \end{pmatrix} \text{ and } \begin{pmatrix} \sin\phi_j \\ -\sin\psi_j \cos\phi_j \\ \cos\psi_j \cos\phi_j \end{pmatrix}.$$

Note that the (t) notation is withdrawn in the definition of the columns of $\mathfrak{R}$ for clarity. In a two-dimensions space ($D = 2$), only the rotation angle $\theta_j(t)$ is considered, leading to a simplified relationship with measured acceleration values,

$$\begin{pmatrix} \gamma_{j,1}(t) \\ \gamma_{j,2}(t) \end{pmatrix} = \begin{pmatrix} \cos\theta_j(t) & -\sin\theta_j(t) \\ \sin\theta_j(t) & \cos\theta_j(t) \end{pmatrix} \begin{pmatrix} \gamma'_{j,1}(t) \\ \gamma'_{j,2}(t) \end{pmatrix}. \tag{2}$$

Once the quantities of accelerations are acquired in the GCS with aid of accelerometer and gyroscope, they are used in the mobility equation to estimate the movement trajectory. To this end, we propose a novel and enforced third-order movement equation as follows,

$$\begin{aligned} \hat{\boldsymbol{x}}_j(t) &= \hat{\boldsymbol{x}}_j(t-1) + \Delta t * \hat{\boldsymbol{\nu}}_j(t-1) + \frac{1}{2} * \Delta t^2 * \boldsymbol{\gamma}_j(t-1) \\ &\quad + \frac{1}{6} * \frac{\boldsymbol{\gamma}_j(t) - \boldsymbol{\gamma}_j(t-1)}{\Delta t} * \Delta t^3, \end{aligned} \tag{3}$$

where $\hat{\boldsymbol{x}}_j(t)$ is the estimated position of the node j at time t, $\hat{\boldsymbol{\nu}}_j(t-1)$ is the velocity vector of the node j at $t-1$ computed at iteration t by

$$\hat{\boldsymbol{\nu}}_j(t) = \hat{\boldsymbol{\nu}}_j(t-1) + \Delta t * \boldsymbol{\gamma}_j(t-1) + \frac{1}{2} * \Delta t^2 * \frac{\boldsymbol{\gamma}_j(t) - \boldsymbol{\gamma}_j(t-1)}{\Delta t}, \tag{4}$$

and Δt is the time interval between two consecutive time-steps. It is worth noting that this model assumes that between two consecutive time-steps $t-1$ and t, the accelerations are linear going from $\boldsymbol{\gamma}_j(t-1)$ to $\boldsymbol{\gamma}_j(t)$, with a slope of $\frac{\boldsymbol{\gamma}_j(t)-\boldsymbol{\gamma}_j(t-1)}{\Delta t}$. With a small Δt, this model works very well, since the approximated acceleration curves becomes very close to the real ones.

Now to solve the problem in the interval framework, we introduce an incertitude $\pm\delta_\gamma$ to the acceleration information $\boldsymbol{\gamma}'_j(t)$ as follows,

$$[\boldsymbol{\gamma}'_j](t) = \Pi_{d=1}^{d=D}[\gamma'_{j,d}](t) = \Pi_{d=1}^{d=D}[\gamma'_{j,d}(t) - \delta_\gamma, \gamma'_{j,d}(t) + \delta_\gamma], \tag{5}$$

where symbol Π indicates the cartesian product. The value of δ_γ should be chosen in the way to have the correct acceleration vector falling within the D-dimensional box $[\boldsymbol{\gamma}'_j](t)$. Let $\tilde{\gamma'}_{j,d}(t)$, $d \in \{1, ..., D\}$, be the correct exact values of the accelerations of the node j at time t, we have a relationship $\gamma'_{j,d}(t) = \tilde{\gamma'}_{j,d}(t) + \epsilon_{\gamma'\, j,d}(t)$, where the acceleration measurement noises $\epsilon_{\gamma'\, j,d}(t)$ is assumed to be gaussian with zero-mean and standard deviation $\sigma_{\gamma'}$. The value of $\sigma_{\gamma'}$ could be obtained by doing a calibration of the accelerometer before the localization. The probability of $\tilde{\gamma'}_{j,d}(t)$ falling within $[\gamma'_{j,d}](t)$ is computed by

$$\begin{aligned} Pr\left(\tilde{\gamma'}_{j,d}(t) \in [\gamma'_{j,d}(t)]\right) &= Pr\left(\gamma'_{j,d}(t) - \delta'_\gamma \leq \tilde{\gamma'}_{j,d}(t) \leq \gamma'_{j,d}(t) + \delta_{\gamma'}\right) \\ &= Pr\left(-\delta_{\gamma'} \leq \epsilon_{\gamma'\, j,d}(t) \leq \delta_{\gamma'}\right) = erf\left(\frac{\delta_{\gamma'}}{\sigma_{\gamma'}\sqrt{2}}\right), \end{aligned} \tag{6}$$

where $erf\,(\cdot)$ is the Gauss-error function. We could ensure at 99.7% that the box $[\boldsymbol{\gamma}'_j](t)$ enclose the real acceleration if incertitude $\delta_{\gamma'}$ is set for instance to $3\sigma_{\gamma'}$. Similarly, an incertitude $\pm\delta_{\Theta_d}, d \in \{1, ..., D\}$, helps schedule the boxes of rotation angles now that the calibration of gyroscope could neither be ignored as

$$[\Theta_j](t) = \Pi_{d=1}^{d=D}[\Theta_{j,d}](t) = \Pi_{d=1}^{d=D}[\Theta_{j,d}(t) - \delta_{\Theta_d}, \Theta_{j,d}(t) + \delta_{\Theta_d}], \tag{7}$$

where $d \in \{1, ..., D\}$, $\Theta_j = (\theta_j, \psi_j, \phi_j)$. Substituting Eq.(5)(7) in the equations given before and by using the interval toolbox, one could compute the acceleration boxes in the GCS, denoted by $[\boldsymbol{\gamma}_j](t)$. Consequently, by rewriting the model Eq.(3) in the interval framework, the mobility estimate of the node position could be boxed as follows,

$$\begin{aligned} [\hat{\boldsymbol{x}}_j]_m(t) &= [\hat{\boldsymbol{x}}_j](t-1) + \Delta t * [\hat{\boldsymbol{\nu}}_j](t-1) \\ &\quad + \tfrac{1}{2} * \Delta t^2 * [\boldsymbol{\gamma}_j](t-1) + \tfrac{1}{6} * \tfrac{[\boldsymbol{\gamma}_j](t) - [\boldsymbol{\gamma}_j](t-1)}{\Delta t} * \Delta t^3, \end{aligned} \tag{8}$$

where $\hat{\boldsymbol{\nu}}_j(t)$ is boxed by $[\hat{\boldsymbol{\nu}}_j](t) = [\hat{\boldsymbol{\nu}}_j](t-1) + \Delta t * [\boldsymbol{\gamma}_j](t-1) + \frac{1}{2} * \Delta t^2 * \frac{[\boldsymbol{\gamma}_j](t) - [\boldsymbol{\gamma}_j](t-1)}{\Delta t}$ and $[\hat{\boldsymbol{x}}_j](t)$ denotes the final estimated box obtained at time t by combining all information. If necessary, the exact first estimate position could be given at the center of the box $[\hat{\boldsymbol{x}}_j]_m(t)$. Nevertheless, we just need the box $[\hat{\boldsymbol{x}}_j]_m(t)$ for the following process.

3.2. Decentralized fingerprinting estimates

In addition to mobility, nodes take advantage of signals RSSIs to be localized. Let $\xi_{x_{j,i}}(t)$ be the RSSI of the signal emitted by the anchor i and received by the node j at time t, $j \in \{1, ..., N_x\}$ and $i \in \{1, ..., N_a\}$. By storing these values in a vector, one obtains the online RSSI vectors denoted by

$$\boldsymbol{\xi}_{x_j}(t) = \left(\xi_{x_{j,1}}(t), ..., \xi_{x_{j,N_a}}(t)\right), \;\; j \in \{1, ..., N_x\}. \tag{9}$$

Each node sends its RSSI online vector to the calculators neighboring it. Let $I_j(t)$ be the set of indices of the calculators neighboring the node j at time t. Now, to solve the problem in the intervals framework, we introduce the incertitude $\pm\delta_\xi$ over the RSSI values. Indeed, in a perfect environment, the RSSI should be constant, with no incertitude, for a fixed traveled distance by the signal. However, in real environments, RSSIs might vary due to interference, noise, multipath, etc. For this reason, and in order to define δ_ξ, several measurements of RSSIs at several distances are needed, before starting the localization. This could be performed in the configuration phase, where a node could be put for a certain duration at each reference position and a set of RSSI vectors is collected for each position. The highest difference between RSSIs vectors is then computed per position and then δ_ξ could be defined as the maximal difference over all the positions. δ_ξ is then a vector of N_a scalar incertitudes, $\delta_\xi = (\delta_{\xi,1}, ..., \delta_{\xi,N_a})$. Another way to compute δ_ξ consists of using the standard deviations of measured RSSIs. Once defined, all RSSIs vector could be rewritten in the interval framework as multi-dimensional intervals, or boxes, by $[\boldsymbol{\xi}_{p_{n.z}}] = [\xi_{p_{n,1.z}}] \times \cdots \times [\xi_{p_{n,N_a.z}}]$ and $[\boldsymbol{\xi}_{x_j}](t) = [\xi_{x_{j,1}}](t) \times \cdots \times [\xi_{x_{j,N_a}}](t)$, where $[\xi_{p_{n,i.z}}] = [\xi_{p_{n,i.z}} - \delta_{\xi,i}, \xi_{p_{n,i.z}} + \delta_{\xi,i}]$ and $[\xi_{x_{j,i}}](t) = [\xi_{x_{j,i}}(t) - \delta_{\xi,i}, \xi_{x_{j,i}}(t) + \delta_{\xi,i}]$.

In order to compute local estimates for nodes positions, the Weighted K-Nearest Neighbors (WKNN) algorithm is applied on calculators [6]. Indeed, for each node j, $j \in \{1, ..., N_x\}$, its neighboring calculators of $I_j(t)$ compute the Euclidean distances $\|[\boldsymbol{\xi}_{x_j}](t), [\boldsymbol{\xi}_{p_{n.z}}]\|$ in the interval framework between the online RSSI box and their reference RSSI boxes. Then, according to the WKNN algorithm, the K indices of reference positions yielding the K smallest distances centers are selected and stored in $I_{p_{j.z}}(t)$, and this for each zone $z \in I_j(t)$. Local position estimates are then computed as follows,

$$[\hat{\boldsymbol{x}}_{j.z}](t) = \sum_{n \in I_{p_{j.z}}(t)} [\omega_{j,n.z}](t) \cdot \boldsymbol{p}_{n.z}, \ \ z \in I_j(t), \tag{10}$$

where $[\omega_{j,n.z}](t)$ is normalized and chosen in the way to be inversely proportional to the RSSI distances as $[\omega_{j,n.z}](t) = \frac{\|[\boldsymbol{\xi}_{x_j}](t), [\boldsymbol{\xi}_{p_{n.z}}]\|^{-\alpha}}{\sum_{u \in I_{p_{j.z}}(t)} \|[\boldsymbol{\xi}_{x_j}](t), [\boldsymbol{\xi}_{p_{u.z}}]\|^{-\alpha}}$, where α denotes a parameter to be tuned. Fusion of all the local estimates gives the second estimated box as follows,

$$[\hat{\boldsymbol{x}}_j]_f(t) = \sum_{z \in I_j(t)} \lambda_{j.z}(t) \cdot [\hat{\boldsymbol{x}}_{j.z}](t), \ \ j \in N_x, \tag{11}$$

where $\lambda_{j.z}(t)$ are the weights in the exponential scheme given by $\lambda_{j.z}(t) = \frac{\boldsymbol{\xi}_{c_{j.z}}(t)}{\sum_{u \in I_j(t)} \boldsymbol{\xi}_{c_{u.z}}(t)}$, where $\boldsymbol{\xi}_{c_{j.z}}(t)$, $z \in I_j(t)$ and $j \in \{1, ..., N_x\}$, are the powers of the signals sent by the nodes to the calculators neighboring them, including their RSSI online vectors. Interval weights could also be obtained by adding incertitude to $\boldsymbol{\xi}_{c_{j.z}}(t)$. The combination is performed at one of the calculators neighboring the node. The second scalar estimate could be picked up at the center of box $[\hat{\boldsymbol{x}}_j]_f(t)$.

3.3. Estimates combination

Since mobility and fingerprinting boxes include the true location of node j at time t, the final position estimate could be obtained by intersecting these boxes as follows,

$$[\hat{\boldsymbol{x}}_j](t) = [\hat{\boldsymbol{x}}_j]_m(t) \cap [\hat{\boldsymbol{x}}_j]_f(t). \tag{12}$$

The final punctual estimate is given by taking the center of the estimated box.

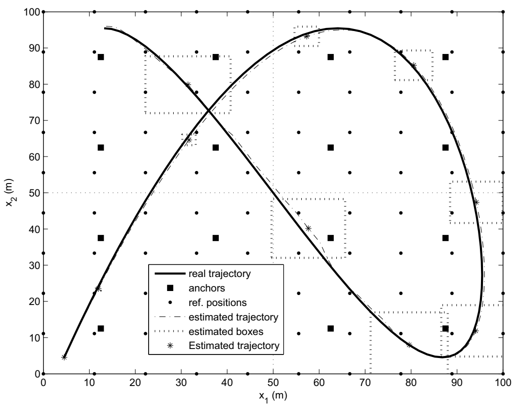

Fig. 3. Illustration of the real trajectory of the node with its estimated one.

4. RESULTS

For illustration, we consider a $2D$ surveillance area of $100m \times 100m$, segmented into N_Z zones, where anchors and reference nodes are uniformly deployed. Nodes travel freely in this region and they are localized independently from each other. So, for simplicity and without loss of generality, only one node is considered for localization and all of the data are simulated. In this section, the nodes are assumed to be rotationally constrained for simplicity, wherever in case of need, the computations could be easily explored for the other case. Node trajectory is generated by defining two acceleration signals, varying over $100s$ with $\Delta t = 1s$ using the sine function, and then by integrating twice their analytic expressions. The initial velocities are set to zero and the node is assumed to be fixed at a known position at the beginning of the localization. The trajectory is shown in solid line in Figure 3.

At the very beginning, we set the numbers of anchors and reference positions respectively to 16 and 100, as shown in Figure 3. In order to generate the simulated RSSIs, we use the Okumura-Hata model [3], as follows,

$$\xi = \xi_0 - 10 \cdot n_P \cdot log_{10} dist, \tag{13}$$

where $\xi_0 = 100dB$ and $n_P = 4dB$. $dist$ denotes the distance between positions of anchors and nodes. A Gaussian white noise is added to the values of accelerations with a standard deviation $\sigma'_\gamma = 0.008m/s^2$, which is equivalent to 5% of the standard deviation of the accelerations. We also add another gaussian white noise RSSIs values with standard deviation $\sigma_\xi = 0.5dB$, which corresponds to 5% of the standard deviation of all RSSIs. The estimation error is the average distance between the exact positions and the estimated ones, over $100s$. A comparison of the estimation errors is shown in Table 1 between using only accelerometer with third-order equation (Accel.), using only fingerprinting in decentralized scheme where $K = 3$ (Fing.) and the proposed combined method in the same conditions with parameter $\alpha = 2$ (Combined). As expected, combining both information leads to more accurate results. Moreover, with less zones, the method is more accurate, since more reference positions are considered per zone. Indeed, with 100 reference positions, one obtains 25 reference positions per zone with $N_Z = 4$ whereas it is around 11 for $N_Z = 9$. By increasing the total number of reference positions to 225, obtaining 25 reference positions per zone for $N_Z = 9$, the estimation results are more accurate. Note that all the results are obtained by executing the algorithm 50 times and averaging the results.

Table 1. Estimation errors in meters with $N_a = 16$.

		Accel.	Fing.	Combined
$N_p = 100$	$N_z = 4$	2.1015	2.2611	**1.0677**
	$N_z = 9$	2.1015	2.7731	**1.7642**
$N_p = 225$	$N_z = 4$	2.1015	1.7432	**0.7521**
	$N_z = 9$	2.1015	1.8226	**0.9325**

We compare afterwards our method to an existing RSSI-based method [10], which proposed a combined K-nearest Neighbors and Fuzzy inference system to improve the positioning accuracy based on fingerprinting method. In this part of simulations, comparison is commanded by testing through two different deployments of the network. One deployment is considered over an area of $100m \times 100m$ as shown in Figure 3 above, while the other one consists of only 4 anchors located at four corners and 25 reference positions, in a $5m \times 5m$ area, as proposed in [10]. Nodes trajectory remains the same. For the former configuration, experimental parameters remain the same as that in the preceding part, whereas in the latter configuration the data are scaled to the area in consideration. Comparison is illustrated as well by estimation errors in meters among three algorithms: the original method FKNN from [10], an updated version of the combination of FKNN and accelerometer data (see section 3.1) and our proposed combined method WKNN+Acc. Results are illustrated in Table 2. Obviously, our method performs better in various configurations of the network.

Table 2. Comparison with Fuzzy Knn method

	FKNN	FKNN+Acc	WKNN+Acc
Configuration 1	2.4926	1.0281	**0.7521**
Configuration 2	0.4794	0.1700	**0.1086**

5. CONCLUSION

This paper proposed an original decentralized localization technique with a third-order mobility model for mobile wireless sensor networks. The proposed method resolves the localization problem using information of accelerometers coupled to gyroscope, fingerprinting and interval analysis. The proposed method computes two interval-estimates and then combines them, leading to position boxes including the real locations of the nodes. Simulation results show that the proposed method outperforms not only the single method of acceleormeter or fingerprinting, but also proves a better performance over another RSSI-based range free method. Future works will handle the localization problem in a more robust way using real data.

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