Using Dempster-Shafer Theory for RSS-based Indoor Localization

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***Abstract*—With the proliferation of the Internet of Things (IoT), employing Received Signal Strength (RSS) as a metric to determine the location of a target (e.g., person or mobile device) is of great interest in terms of cost and ease of implementation. Indeed, RSS measurements can be easily obtained for most off-the-shelf devices, such as WiFi- or ZigBee compatible devices or sensors. This paper deals with the indoor localization problem in wireless sensor networks (WSNs) and proposes a new approach for radio signal propagation modelling and localization estimation, that accounts for the imperfection of RSS measurements and the reliability of RSS sources by using the Dempster-Shafer Theory (DST). In the signal propagation modelling, key information regarding the geometry of indoor environment that is divided into zones separated by walls (zoning), are considered. Based on the number of walls, the RSS irregularities are estimated using different distance intervals, which are weighted by a probability density determined experimentally. To estimate the location of a target node, the PCR6 rule is used to combine the belief masses of the positions obtained from the probability density. In order to evaluate the performance of the proposed approach, an experimental WSN has been deployed in a living apartment. The obtained results demonstrate that the proposed approach improves the localization accuracy compared to the case without zoning. Moreover, the obtained localization mean error proves the feasibility of a precise localization of humans in indoor environments in the case of Ambient Assisted Living and Social Robotics applications.**

I. Introduction

Context awareness is a key feature that makes smart systems able to self-adapt their services to users and environmental changes. Location is a centric attribute of users' context, which can also be exploited to better estimate and understand the other contextual attributes such as activities, interactions, emotions, mental states, etc. Developing high precision localization techniques for indoor environments has witnessed a big interest in particular for Ambient Assisted Living and Social Robotics applications. Several surveys have been published recently, which report the main approaches of the literature [1] [2] [3] [4] [5]. Most of these approaches propose to exploit wireless communication techniques such as Radio Frequency Identification Device (RFID), Bluetooth Low Energy (IBeacon), Zigbee/6lowpan, WiFi, Visible Light (Lifi) [2], and recently LoRa, Sigfox, NB-IoT [6], which support long-range, low power and low throughput communications but can enable more possibilities and complementarity between indoor as well as outdoor applications. The Received Signal Strength (RSS) is the most commonly used metric for developing indoor localisation methods [7]. This metric is of great interest in terms of cost and ease of implementation. RSS measurements can be easily obtained from any node of any kind of wireless communication network and do not require neither transmission scheduling or synchronization at the node level. Generally, to estimate the position of a target node in a WSN, RSS-based indoor localization techniques exploit the RSS measurements received from emitter nodes straightly or the distances between emitter nodes and the target node (receiver node) estimated from propagation models. In geometric techniques such as trilateration and triangulation, the distances between the emitter nodes and the target node are used to estimate the position of the target node. However, the wide fluctuation of radio signals in indoor environments makes the prediction of the RSS very challenging. The main problem in estimating the distance between the nodes is related to the fact that the RSS measured in an indoor environment is nonlinear with distance. In addition, RF signals are subject to interference and attenuation effects due to several phenomena such as multipath, reflection, channel fading, deflection and diffraction. These effects are increased when the indoor environment is highly furnished and separated by different types of walls.

This paper proposes an indoor localization approach that deals with the imperfection of RSS information obtained from a wireless sensor networks (WSNs). The major aspects of RSS imperfection can be either imprecision or uncertainty. Imprecision refers to the information content and measures a quantitative default of knowledge or measurement, (e.g., the same distance corresponds to an interval of RSS values) [7]. In contrast, uncertainty refers to the degree of truth of information and characterizes how much the information conforms to the reality, which results from a lack of information about the sensors and their deployment conditions in the real world. The RSS modelling methods of the state of the art often assume that the received signal strength is proportional to the inverse square of the distance between the transmitter node and the receiver node and the imperfections correspond to a Gaussian noise. However, in practice, the results of real measurements in WSN demonstrate that the aforementioned assumption is not

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realistic [8] [9]. Therefore, it is important to take into account the imperfection of RSS measurements more finely and model the reliability of the RSS measurements to increase the localization accuracy. In this paper, we propose to use Dempster-Shafer Theory (DST) [36] to handle the imperfection of RSS information and develop a robust localization technique. The DST theory allows representing and fusing the information provided by more or less reliable and conflicting sources on the same hypothesis of a set called the frame of discernment. This study is in the continuity of the research activity initiated in [7] that employs DST and consider Non-Gaussian probability density functions to model RSS deviations, as a more realistic option for WSN in indoor environments. In the signal propagation modelling method proposed in this paper, key information regarding the geometry of the indoor environment that is divided into zones separated by walls, are considered. Based on the number of walls crossed by the RF signal in the indoor environment, the RSS irregularities are estimated using different distance intervals which are weighted by a probability density determined experimentally. After defining the frame of discernment, which corresponds to the different positions in the environment, a belief mass is assigned to each position depending on the distance intervals. The position of the target node is estimated based on the belief masses which are combined using the the Proportional Conflict Redistribution rule (PCR6) [39]. Unlike [7] where the Dempster rule (DR) is used [36] to uniformly redistribute the mass resulting from the conflict in the combination step, the PCR6 rule used in the proposed approach is better suited to handle high conflict between sources, generated by the use of distance intervals in the assignment of belief masses. Moreover, in the decision-making step, the maximum of credibility mode is preferred to the merging mode proposed in [7] since the latter is more complicated to implement in practice. The proposed approach is evaluated based on experimental dataset of more than 1000 RSS samples that have been captured in a living apartment from 11 reference positions. The obtained results demonstrate that the proposed approach improves the localization accuracy in terms of mean and median metrics.

The paper is organized as follows: Section II presents the related work on RSS-based indoor localization techniques with a focus on propagation models proposed in the literature. Section III describes the RSS modelling method while Section IV details the exploitation of DST and the PCR6 rule to estimate the most accurate position of target node. Experiments and the obtained results are discussed in Section V. Finally, a conclusion and future research directions are presented in Section VI.

II. Related Work

This section analyzes the main RSS-based indoor localization techniques proposed in the literature, which can be divided into four main categories. The first one refers to the Proximity-based localization techniques where the target node position is estimated by exploiting its closeness to known reference nodes (anchors nodes). The distance between the reference nodes and the target node are determined from RSS measurements by using, for instance, RFID [10] or WSN [11] technologies. Proximity-based localization techniques are easy to implement and does not require any complex algorithms. However, their accuracy depends mainly on the density and distribution of the reference nodes. The second category includes the geometric techniques such as Multilateration, Centroid and Min-Max, which allow estimating the target node position by exploiting the distances separating the target node and the reference nodes; these distances are estimated using RSS measurements and propagation model.

The third category is fingerprint-based localization techniques [2] which operate in two phases. In the first phase, called mapping phase, RSS measurements at known and fixed locations are stored in a fingerprint database. In the second phase, called operational phase, the RSS values measured at the current location are compared to the ones in the fingerprint database. The target node position is estimated either by finding the best matching between the RSS measurements and the pre-stored ones [30] or through inference that takes into account the distributions of RSS measurements in the radio map of the localization area [31] [13]. Fingerprint-based localization techniques based on deep learning architectures have been also proposed in the latest years. In [32], Deep neuronal networks (DNN), Deep Belief Network (DBN) and Gaussian-Bernoulli-DBN (GB-DBN) algorithms are implemented to increase the estimation accuracy and reduce generalization error in dynamic indoor environment. Fingerprint-based localization techniques achieve better localization accuracy compared to proximity and geometric techniques. However, it require dense training coverage to build fingerprint database, and implicitly, high manual cost and efforts.

The last category include localization techniques based on computational intelligence methods or machine-learning methods such as genetic algorithm (GA), support vector machine (SVM), fuzzy logic (FL), and DST [7], [12], [13]. RSS metric is used with certain classification techniques in wireless localization through classification. SVM model is exploited in [33] to determine the region degree membership of the target node based on RSS measurements, and a WiFi localization system rule-based FL is proposed in [34] to predict the location in terms of building's zones classification using filtered RSS inputs.

In practice, the use of the RSS measurements for localization induces several difficulties in the context of an indoor environment due to the occurrence of phenomena of reflection, diffraction, absorption, and multipath fading inherent to radio waves propagation. This makes it difficult to build a reliable radio signal propagation model in the context of an indoor environment. To model the relation between RSS measurements and the distance between nodes, the commonly used propagation models are: log-distance path-loss model (LDPL), Two-ray propagation model (TRP), Log-distance path-loss shadowing model (LDPLS). The LDPL model [14] assumes an unobstructed LOS path through free space between the transmitter node and the receiver node, thus

RSS is inversely proportional to the square of the distance the distance between the transmitter node and the receiver node. The LDPL model parameters are generally estimated in calibration phase using regression methods whose performance depend on the quality and quantity of the RSS measurements. Multilateration [15], Min-Max [16], ROCRSSI and Weighted Centroid Localization (WCL) [17] are examples of geometric localization techniques exploiting the LDPL model to estimate the target node position. To improve the localization accuracy, other works apply fuzzy logic inference to distances estimated via the LDPL model before applying geometric techniques [18] [19]. In [20] [21], fuzzy logic inference is applied directly on RSS measurements to weight anchor nodes positions and the centroid algorithm is then used to estimate the target node position. TRP model is a modified version of the LDPL model taking into account the effect of reflection of signals. In [22], the TRP model is used to build a WiFi RSS map to account for absorption and reflection characteristics of various obstacles; position estimates are then computed using Bayesian filtering on sample sets derived by Monte Carlo sampling. Experiments showed that the TRP model gives more accurate prediction at long distance than the LDPL model. However, in the context of an indoor environment where rooms are only a few square meters in size, the two models are equivalent [23]. Although the LDPL model is simple to use, it does not adequately account for the propagation characteristics in indoor environments. Thus, the LDPLS model was proposed to characterize the variation of RSS over distance due to path loss and shadowing effects. The latter are due to the obstacles that attenuate signal power due to absorption, reflection, scattering, and diffraction phenomena [24]. To characterize the attenuation caused by shadowing, a zero-mean normal random variable is generally used [14]. In [25], the authors introduce a parameter to take into account the Non-Line-of-Sight (NLOS) effect and a zero mean Gaussian variable to take into account the multi-path effect due to shadowing. The LDPLS model is used for distance estimation in geometric localization techniques such as WCL [9]. Other works exploit also the LDPLS model in fingerprint-based localization techniques to take into account the variability of RSS measurements [26] [27] [28]. In [12], the authors propose a localization technique combining the DST with the LDPLS model. Belief masses are assigned to each position in the localization area based on the RSS measurements and the probability the target node is at this position. The LDPLS model where the RSS noise is modelled as a Gaussian distribution, is exploited to calculate this probability. Besides, DR is used to iteratively combine the pieces of evidence whereas the maximum of credibility is exploited as the decision-making mode. RSS noise induced by the number and type of obstacles (walls, floors, doors, etc.) along the transmission path is also considered in [23] [29]. In the case of the LDPLS model, assuming that LOS and NLOS signals can be differentiated in indoor environments is difficult to implement in practice. The previous analysis clearly shows that the aforementioned propagation models are highly dependent to the environment structure, and require high manual cost and efforts in terms of the calibration phase. Besides, in most of localization techniques proposed in the literature, the RSS noise is assumed obeying to a Gaussian distribution, which is not realistic.

III. RSS Modeling

In this section, a realistic modelling of the variability of RSS measurements due to interference and attenuation phenomena that affect signal propagation in indoor environments, is proposed. The proposed modelling is an extension of our previous work [7] where two intervals of distances $I_1 = [d_{min}, d_{mean}]$ and $I_2 = [d_{mean}, d_{max}]$ are associated with each RSS measurement for better accounting the RSS variability; d_{min}, d_{mean} and d_{max} represent the estimated minimum, mean and maximum distance deviations respectively. The distances of each interval are weighted by probability densities in order to represent the imprecision on the RSS measurements. The distance deviations estimates are obtained by interpolating the minimum and maximum RSS measurements via the power function for d_{min} and d_{max}, and by interpolating the average RSS measurements via the sinus function for d_{mean}. The estimates obtained from the RSS measurements collected in our experimental environment (living apartment) are shown in Fig. 1.

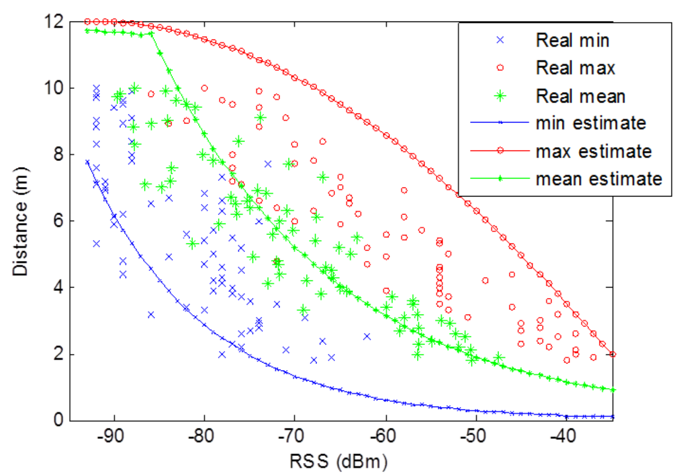

Fig. 1. Estimates obtained in our indoor environment

The probability of measuring an RSS value v at a given distance d is calculated using the probability density function pd of (1):

$$pd\,(v|d) = \varphi \arctan\left(\alpha_k \tilde{d} + \beta_k\right) + \xi \qquad (1)$$

The density function parameters are estimated during the calibration phase. The term $\tilde{d}$ corresponds to the distance deviation that separates the transmitter and the receiver knowing the value v, the coefficients φ, α_k and β_k, with $k = \{1, 2\}$, depend on the bounds of the distance intervals I_1 and I_2 of v. The term ξ defines the probability to measure the value v at the distances d_{min} and d_{max} ($\xi = p\,(d = d_{min}) = p\,(d = d_{max})$).

This approach has the advantage to not distinguish between physical phenomena (reflection, diffraction, absorption etc.), but rather to take them into account at the same time implicitly. The radio signal propagation in indoor environments is strongly affected by the various obstacles, in particular the walls separating the rooms, which is not taken into account in our previous modelling [7]. In the present study, we propose to model the RSS measurements using additional distance intervals in the case where the received signal passes through several walls. The proposed modelling is detailed in the following subsection.

A. *RSS vs number of walls*

The proposed RSS modelling takes into account the presence of walls in the indoor environment considering that this environment is divided into several rooms called here zones separated by walls (zoning). This modelling approach considers also that each zone is equipped with one to several sensor nodes, which transmit signals throughout the WSN. In order to estimate the influence of the number of walls on the radio signal propagation, we collected set of RSS measurements at different representative distances in the experimental environment (living apartment). Fig. 2 (a) shows RSS measurements as a function of distance and the number of walls separating the transmitter from the receiver. It is worth to mention that the signal becomes more fluctuating and its power decreases when the number of crossed walls increases. Therefore, the signal received from a sensor located within the same zone (living room, bedroom, ...) is less disturbed compared to a signal coming from another zone in the case of two similar distances separating the receiver node from each transmitter node. The mean distance deviation estimates d_{mean}, depicted in Fig 2 (b) are obtained by interpolating the mean RSS measurements using the power function by varying the number of walls in the set 0,1,2.

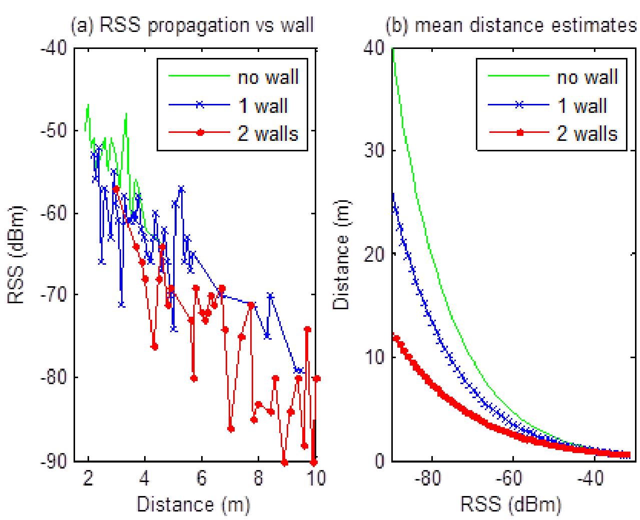

Fig. 2. (a) Signal propagation according to the number of walls crossed, and (b) mean distance estimates according to the number of walls crossed

In the same way as for the distances d_{mean}, estimates of distances d_{min} and d_{max} are obtained by varying the number of walls. Fig. 3 (a) shows the distance estimates for signals not crossing walls while fig. 3 (b) and fig. 3 (c) show distance estimates for signals crossing respectively 1 and 2 walls.

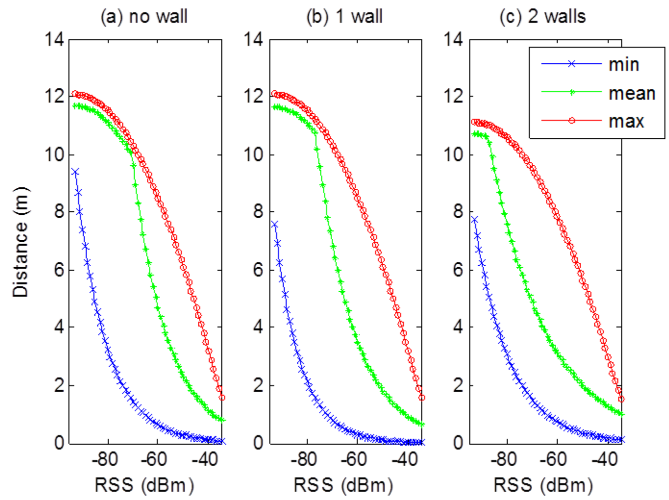

Fig. 3. Signal propagation modeling according to number of walls in indoor environment

B. *Weighting of distance intervals*

Since the distance intervals corresponding to an RSS measurement are not the same inside and outside a given area and the estimates of the deviations depend not only on the distance but also on the number of walls crossed by the signal received, the weighting of the distances also depends on the number of crossed walls. Let be $Z = \{z_1, \ldots, z_l\}$ the set of zones composing the environment, $S = \{s_1, \ldots, s_k\}$ the set of anchor nodes and z_{s_j} the zone where the node s_j is deployed. Algorithm 1 represents the pseudo-code of the probability densities assignment to the distances per zone for each RSS value.

Algorithm 1 probability assignment per zone

Require: zones Z, sensors S
Ensure: // assign probability to zone z_i depending on s_j
  for each z_i **do**
    for each s_j **do**
      if $s_j \in z_i$ **then**
        $zone\_in\,(z_i, s_j)$
      else if z_{S_j} adjacent to z_i **then**
        $zone\_out\_1\,(z_i, s_j)$
      else
        $zone\_out\_2\,(z_i, s_j)$
      end if
    end for
  end for

- $zone\_in\,(z_i, s_j)$: calculates the probability densities of the distances between the receiver node and the anchor node knowing that both nodes are in the same zone z_i.

- $zone\_out\_1\,(z_i, s_j)$: calculates the probability densities of the distances between the receiver node and the anchor node, where the anchor node s_j is in a zone z_{s_j} adjacent to the zone z_i where the receiver is located.
- $zone\_out\_2\,(z_i, s_j)$: calculates the probability densities of the distances between the receiver node and the anchor node, where the anchor node s_j is in a zone that is not adjacent to zone z_i where the receiver is located.

IV. DST APPLIED FOR INDOOR LOCALIZATION

Dempster-Shafer Theory (DST), introduced by Dempster in 1967 [35] and formalized by Shafer in 1976 [36], allows representing both imprecision and uncertainty using the functions of mass, plausibility and belief. The mass functions are defined on all subsets of the frame of discernment and not only on singletons as in the theory of probabilities. DST is applied in four steps: definition of the frame of discernment, definition of the mass functions, belief masses combination, and decision-making.

A. Frame of discernment

In general, the mobile localization problem is to estimate the position of a mobile moving in the environment. In our case, the indoor localization space is represented by a set of positions constituting a grid of possible solutions or hypotheses h_i for the mobile. Accordingly, the frame of discernment is the finite set of mutually and collectively exclusive assumptions given by $\Theta = \{h_1, h_2, \ldots, h_k, \ldots, h_n\}$. The power set is defined as $2^\Theta = \{\emptyset, \{h_1\}, \ldots, \{h_i\}, \ldots, \{h_1, h_2\}, \ldots, \{h_i, \ldots, h_n\}, \Theta\}$.

B. Mass Assignment

A mass function m is defined as a function of 2^Θ in $[0, 1]$. In general, it is imposed $m(\emptyset) = 0$ and a normalization of the form:

$$\sum_{A \subseteq \Theta} m(A) = 1 \tag{2}$$

Given a mass function m, the belief (credibility) function bel is defined as :

$$\forall A \in 2^\Theta, bel(A) = \sum_{B \subseteq A, B \neq \emptyset} m(B) \tag{3}$$

This function allows measuring the total confidence that we have in a subset A. Similarly, the plausibility function pls of 2^Θ in $[0, 1]$ defined by:

$$\forall A \in 2^\Theta, pls(A) = \sum_{B \cap A \neq \emptyset} m(B) \tag{4}$$

This function is used to measure the maximum confidence that we can have in a subset A.

In the context of localization in WSN, we assume that the target node can be -at any time- at a given h_i position in the localization area. In the case where the target node is not at the position h_i, it is necessarily located at one of the other positions h_i^c, which correspond to the complement of h_i. In the case of ignorance, the target node may be located at any position of Θ. Thus, let's consider the subsets h_i, h_i^c and Θ as the only focal elements in 2^Θ. A focal element is an element whose mass is greater than 0. The belief mass defined from the a priori probability densities $pd(v|d)$ is distributed over the 3 focal elements. This probability is denoted by $p\,(s_j|h_i)$ to better express that the RSS value v measured at position h_i corresponds to the signal coming from the source s_j. Then, based on the model proposed in [37], the belief masses $m_i^j(.)$ attributed to the focal elements by introducing a degree of reliability α_{ij} relative to the source s_j on the hypothesis h_i are given by (5), (6) and (7).

$$m_i^j(h_i) = \frac{\alpha_{ij} \Re_j p\,(s_j|h_i)}{1 + \Re_j p\,(s_j|h_i)} \tag{5}$$

$$m_i^j(h_i^c) = \frac{\alpha_{ij}}{1 + \Re_j p\,(s_j|h_i)} \tag{6}$$

$$m_i^j(\Theta) = 1 - \alpha_{ij} \tag{7}$$

where $\Re_j \geq 0$ is a normalization factor. If it is equal to zero, only the reliability of the source is taken into account, otherwise the information is also taken into account. The choice of this factor is arbitrary but to obtain the least specific belief function possible, we take the maximum probability in the range of distances $I_1 \cup I_2$ defined previously for each RSS value. The reliability parameter α_{ij} is obtained from the distance d_{ij} between sensor s_j and position h_i as follows (8) :

$$\alpha_{ij} = \begin{cases} 1 & \text{if } |d_{ij} - d_{mean}\,(v_j)| \leq d_{conf} \\ \sqrt{\frac{d_{conf}}{|d_{ij} - d_{mean}(v_j)|}} & \text{if } |d_{ij} - d_{mean}\,(v_j)| > d_{conf} \\ & \text{and } d_{ij} \in I_1 \cup I_2 \end{cases} \tag{8}$$

In the case where the distance $d_{ij} \notin I_1 \cup I_2$, the source s_j is eliminated and the combination is done with the rest of the sources. Otherwise, the value of α_{ij} is calculated with respect to a confidence distance d_{conf} determined experimentally for which the source s_j is considered completely reliable for the position h_i.

C. Combination of information

In the presence of several sources of information, it is interesting to combine the knowledge of each source in order to extract a global knowledge about the real-world and apply a decision-making mode. For this purpose, various combination rules have been proposed in the literature [38]. In this paper, we exploit the PCR6 rule [39], which is one of the most efficient and widely used combination rules for solving conflicts. PCR6 is used to distribute the mass of belief resulting from the conflict on the focal elements involved in the conflict [40]. The redistribution of the partial conflicting masses in a proportional way to the hypotheses (even non singleton) in the case of two mass functions m_1 and m_2, where $B_1, B_2, C \in 2^\Theta$, is given by (9):

$$m_{pcr6}(A) = \sum_{B_1 \cap B_2 = A} m_1(B_1) m_2(B_2) + \sum_{A \cap C = \emptyset} \left(\frac{m_1(A)^2 m_2(C)}{m_1(A)+m_2(C)} + \frac{m_2(A)^2 m_1(C)}{m_2(A)+m_1(C)} \right) \quad (9)$$

The denominators $m_1(A)+m_2(C)$ and $m_2(A)+m_1(C)$ are non-zero. Applying this rule to an RSS vector gives a mass for each hypothesis that will be exploited for decision-making.

D. Decision-making

DST proposes several modes for decision-making [41]. The most commonly used are the maximum of credibility, the maximum of plausibility and the maximum of pignistic probability. In this study, we choose the maximum of credibility mode which is pessimistic or cautious since an RSS vector, can be measured in several positions of the environment as shown in Fig. 4.

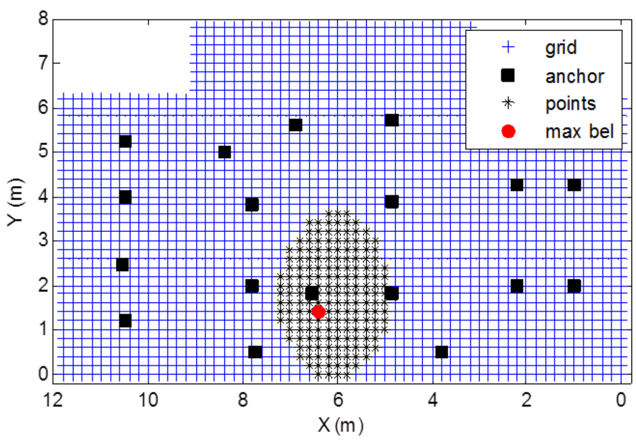

Fig. 4. Positions of the grid (*) where the target may be when it received a vector of RSS measurements

The diagram in Fig. 5 summarizes the methodology of the proposed approach to estimate the position of a target node in the indoor environment.

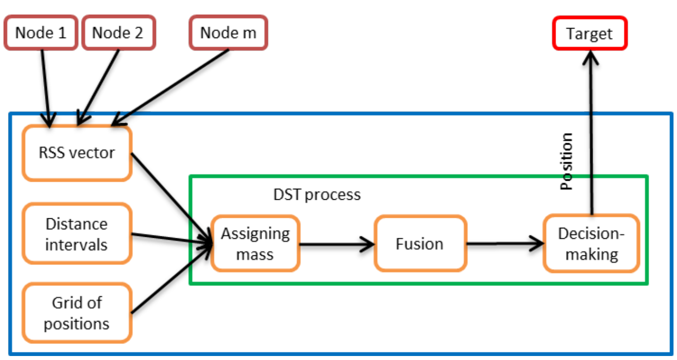

Fig. 5. Diagram representing the localization process based on the Dempster-Shafer Theory Theory

V. Experimentation and results

The experiments were carried out in a typical living apartment composed of a living room, two bedrooms (one of which is empty), a bathroom, a WC and a corridor. The dimensions of the space are 11.80 m x 70.80 m x 2.50 m. A 6Lowpan WSN composed of 19 TelosB sensor nodes has been deployed on the ceiling in such a way as to cover the entire area as shown in Fig. 6.

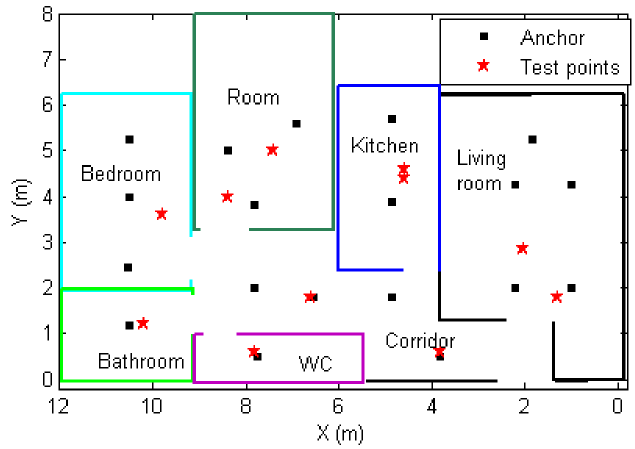

Fig. 6. Sensor nodes deployment plan in the experimental environment.

To evaluate the accuracy of the proposed approach, we collected more than 1000 RSS samples in 11 different representative positions in the apartment. We used statistical metrics and CDF (Cumulative Density Function) curves to make this assessment.

The results obtained in all the tests are presented in Table I and Fig. 7. One can observe that zoning of the environment improves localization accuracy in terms of mean, median and standard deviation compared to the case without zoning. The mean localization error is 1.25 m. The latter is sufficient for Ambient Assisted Living applications since most of the RSS-based indoor localization systems dedicated to this kind of applications have mean accuracy from 1 m to 2 m according to [2].

TABLE I
Comparison of the localization error statics for zoning and non-zoning environment

	zone	no zone	Improvement (%)
min	0.00	0.00	0
max	4.88	4.60	-6
mean	1.25	1.53	19
median	1.13	1.26	11
std	0.69	0.98	30

VI. Conclusion

In this paper, a new RSS-based indoor localization approach based on the Demspter-Shafer theory is proposed to handle the imperfection of RSS measurements and the reliability of the RSS sources. A realistic modelling of the variability of RSS measurements in indoor environments, is proposed. This modelling takes into account the number of walls crossed by the RF signal received in an indoor environment composed of

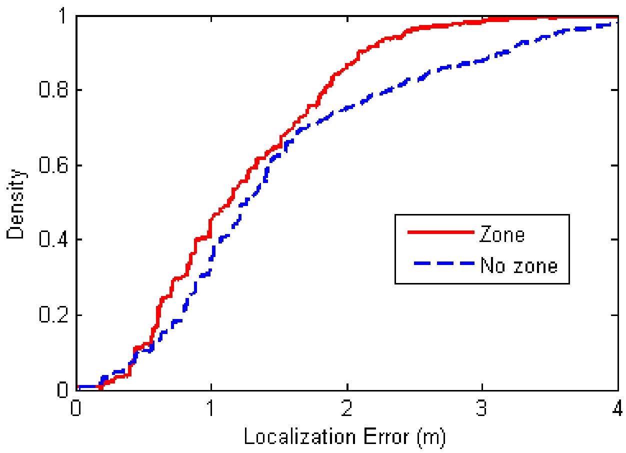

Fig. 7. Localization error CDFs comparison

zones separated by walls. The RSS irregularities are estimated using different distance intervals which are weighted by a probability density determined experimentally. DST theory is used to locate the target node by assigning belief masses to each position in the localization area based on the zoning. The PCR6 combination rule is exploited to estimate the most plausible position of the target node. The results, obtained from experiments conducted in a living apartment, demonstrate clearly that taking into account the geometry of the environment in terms of number walls and zones crossed by the RF signals, improves the localization accuracy. The future research works concern the adaptation of the RSS modelling and localization estimation approach to take into account trajectories than individual positions and ensure by the way the continuity of the localization from WSN to large scale IoT environment enabled by long-range, low power and low throughput communications networks such as LoRa, Sigfox, NB-IoT. In this perspective, additional environmental parameters will be considered such as the impact of the construction materials used in the walls and the doors, which alter the RF signals at different levels. In addition, the dynamics related to the mobility of humans in the indoor environment such as openings and closing doors will be considered also since it has an impact on the line of sight of the RSS sources, which become visible in other zones and must be considered in the localization estimation process.

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