Abstract—Wireless sensor networks can be used in habitat monitoring for detecting fire, in disaster for helping rescue teams and in agriculture for sensing humidity. Node localization is essential for some important sensor network applications. Despite the high relative accuracy of some localization algorithms, node localization is still an open research area, due to the physical phenomena such as attenuation, reflection, diffraction, scattering and so forth. The current developed algorithms have different accuracy when are tested under dissimilar environments. We propose to use Smart Beacon Nodes (SBNs) to infer the Obstruction Level Indicator over an occupied area, then, use this indicator for estimating the distance among nodes. In our experimental simulation, SBNs decrease the node localization error of Triangular Centroid Localization and Weighted Centroid Localization up to 18%.

Keywords—wireless networks; distance estimation; obstacle estimation; position location; link quality indicator; received signal strength indicator.

I. INTRODUCTION

A Wireless Sensor Network (WSN) is formed by various small devices (nodes) capable of collecting information from the environment such as temperature, vibration, humidity, sound, light and motion. Besides, their wireless communication allows rapid deployment of a network composed of hundreds of them. A WSN in habitat monitoring can detect fire, in agriculture can sense humidity and in disaster events (earthquake) can help rescue teams. Node localization is an essential for some applications. Actually there are diverse Localization Algorithms (LAs), all them can be classified in two wide branches, range-based LAs and range-free LAs. Range-based LAs use the distance or angles such as AoA [1], RSS [1], ToA [1], TDoA [1], SpotON [2], Pintr [3] and GPS. Nevertheless, GPS cannot work indoors, it needs line-of-sight and it is not a best solution from an economic perspective. Range-free LAs use only the content of received messages such as APIT [1], [4]; Centroid [1], [5]; Bounding box [1] and DV-Hop [1], [6]. Also the LAs that have been arisen between these two large classifications such as Triangular Centroid Localization (TCL) [7], Weighted Centroid Localization (WCL) [8] and the work presented in [9]. All the last algorithms have different accuracy and approach; however node localization is still an open research area due to the wave propagation irregularity. This leads the inclusion of accurate models of the physical phenomena into LAs such as attenuation, reflection, diffraction and scattering, just to name a few, for greater detail see [10]. In general, all algorithms are affected by these conditions in lesser or bigger degree. For instance, Centroid has a maximum error outdoors of 4.16 meters and a maximum error indoors of 22.3 meter according experimental results of the authors. From this, some authors develop LAs to be executed in specific places for getting high accuracy such as RADAR [11].

In order to improve the node anywhere, we propose Smart Beacon Nodes (SBNs), which provide the Obstruction Level Indicator (OLI) over an occupied area; LAs use this indicator for better estimating of the distance among nodes. SBNs do not increase the implementation cost, due to they do not require any special hardware or synchronization time. Our first approach opens the possibility of executing the LAs indoors and outdoors with the same accuracy.

The paper is organized as follows. Section 2 presents the related work, section 3 details Obstruction Level Indicator estimation, section 4 shows the experimental results and finally the work conclusion in section 5.

II. RELATED WORK

Along this paper, the term beacon nodes is used for specifying those nodes whose physical position is known and non-beacon nodes for those nodes with unknown position physical.

There are diverse approaches for estimating the distance between nodes by using Received Signal Strength Indicator (RSSI) [12],[13],[14]. On this basis alone, various localization algorithms have been developed. In [12], authors improve the estimation by filtering the measured RSSI through optimized standard deviation and packet loss limits. On the other hand, in [13] is presented a study of the RSSI, where authors conclude that RSSI is bad distance estimator in buildings; as a matter of fact, indoor node localization is a hard task for LAs based on RSSI such as is shown in [2],[7],[8],[11]. In general, these kinds of methods suffer problems of multi-path fading, background, interference and irregular signal propagation.

In [7], authors address the node localization by using trigonometric figures and the well-known hot-cold game.
method uses hypothesis testing for estimating the distance between nodes. That is, in online process one sample of RSSI/Link Quality Indicator (LQI) from a couple of nodes can be associated with one population. Each population represents the recorded RSSI/LQI at each meter of separation between nodes (from 0 to 18 meters). In order to show the high accuracy of TCL, the distance among nodes is assumed as accurate; under this condition, the average localization error is 0.001 meters. This algorithm and WCL [8] have been presented as an extending of Centroid [5], in which a non-beacon node \( i \) estimates its physical position \( P_i \) in two planes \((x,y)\) by averaging the positions of the \( n \) heard beacon nodes \( B_j \). The last can be expressed as the equation (1).

\[
P_i(x, y) = \frac{1}{n} \sum_{j=1}^{n} B_j(x, y)
\]

(1)

WCL works as follows. In equation (2), a non-beacon node \( i \) estimates its position \( P_i(x, y) \) by averaging of the position of the \( n \) heard beacon nodes \( B_j \). For each \( B_j \), a weight \( W_j \) is assigned. In equation (3), the variable \( W_j \) is obtained by considering wave attenuation; the distance estimation \( d_{ij} \) is estimated by the suffered variations of the LQI regarding the separation between nodes \( i \) and \( B_j \); the distance \( d_{ij} \) is raised to a higher power of \( g \). For a concentric wave expansion with a linear characteristic of the receiver and a uniform density of the beacon nodes. The variable \( g \) takes integer values ranging from 1 to 5 in order to determine the optimal \( g \).

\[
P_i(x, y) = \frac{\sum_{j=1}^{n} (W_{ij} \times B_j(x, y))}{\sum_{j=1}^{n} W_{ij}}
\]

(2)

\[
W_{ij} = \left( \frac{d_{ij}}{\rho} \right)^g
\]

(3)

In the experimental result of the authors, WCL gets the better outcome when \( g = 1 \) and the coverage range is 10 meters; and \( g = 3 \) and coverage range is 30 meters. In this method the distance estimation has been done empirically such as SpotON [2] and RADAR [11]. SpotON is a tagging technology for three dimensional locations; it can be extended as SpotON and RADAR [11]. SpotON is a tagging technology for three dimensional locations; it can be extended as SpotON and RADAR [11]. In our experimental result, we show that by using a simple OLI as \( \rho \) in the combination of Log-normal and Rayleigh distribution for other cases.

III. OBSTACLE LEVEL INDICATOR

To the best our knowledge there is not a single LA that considers all the possible factors anywhere. For instance the wave propagation, hardware constraints, network density and network traffic, mainly. A wireless network might have quite different behavior in each part of it. We think in the following idea, if a single LA “could know” the behavior of the wireless network in each part; it can take advantage of this information for improving the node localization estimation. With this we want to introduce Smart Beacon Nodes. We name them as SBNs because they can interpret the variation of the RSSI/LQI for inferring the Obstacle Level Indicator among them. From this information, a better distance estimation among node and an approximation of the WSN behavior can be achieved. Unlike common beacon nodes, which only transmit their information to specific nodes or to everyone (broadcast mode).

By using the network simulator AvroraZ [17] we have established the topology of the WSN along with obstacles, the functionality of nodes have done in TinyOS [20]. Hereafter, the symbol \( \rho \) is used for representing the obstacles, in order to maintain the symbol originally assigned by author of AvroraZ. The variable \( \rho \) represents the number of people per square meter in the coverage range of each node. For instance, if \( \rho = 0.05 \) there are 0.05 people per square meter, that is one person per every 20 square meters. Authors make a good approximation of the wave behavior of the chip CC2420 under diverse environment conditions. The indoors model was developed considering the nodes on ceiling, walls or sometimes even on desks. The model uses Rice distribution when \( \rho \) is equal to zero and the combination of Log-normal and Rayleigh distribution for other cases.

For establishing Obstacle Level Indicator values, first we have simulated 2 nodes micaz at base-D meters of separation between them, where base-D takes positive integer values from 1 to 18. For each base-D, the variable \( \rho \) has been changed incrementally in 0.01 from 0.0 to 0.99. For each value of \( \rho \), 10 simulations have been done; a database was created with a total of 19,000 achieved simulations. From the generated database, a simple Unknown Distribution (UD) has been created for each 10 increments of \( \rho \). This process was done for each base-D. It can be expressed by OLI = UDbase-D, \( \rho \). For instance, OLIbase-D = UDbase-8, \( \rho \), that is the UD of 8 meters with \( \rho \) = [0.5, 0.59]. We also have created an UD of each simple \( \rho \) of each base-D. For example, OLIbase-D = UDbase-6, \( \rho \), that means, the UD of 6 meters with \( \rho \) = 0.77. In this form, we can identify a group of 10 incremental \( \rho \) as OLIbase-D and a simple \( \rho \) as OLIbase-D.

In our experimental result, we show that by using a simple \( \rho \), the node localization error can be decreased up to 18% and making a cluster of simple \( \rho \) (OLIbase-D) up to 15%. We cannot consider the OLI only in the intersection of the coverage ranges of nodes, because the network simulator takes the major \( \rho \) between them.
The Figure 1 depicts the behavior of the recorded RSSI of two nodes micaz at 5 meters and 10 meters of separation between them with $\rho = [0.0, 0.99]$. The value of the RSSI at 5 meters with $\rho = 0.92$ is almost the same value of the RSSI at 10 meters with $\rho = 0.0$. Under this condition, some localization algorithm can estimate the distance between a pair of nodes of 5 meters as 10 meters. These kinds of situations are counterattacked by the transition of OLI.

![Figure 1. RSSI for base-D = 5 and base-D = 10 with $\rho$ from 0.0 to 0.99.](image)

The SBNs apply Hypothesis Testing (HT) for selecting the better $\rho$ for each couple of beacon nodes. The Table I shows the acceptance region and confidence level of the statistical value $z$ regarding the RSSI/LQI for all UD. The values were defined empirically from the database generated by recorded RSSI/LQI. The Algorithm I shows the technique for estimating OLI among SBNs by using HT.

<table>
<thead>
<tr>
<th>TABLE I. CONFIDENCE LEVELS AND ACCEPTANCE REGIONS</th>
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<tbody>
<tr>
<td>RSSI</td>
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<tr>
<td>Acceptance region</td>
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<td>Confidence level</td>
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</table>

ALGORITHM I. ESTIMATING THE OLI AMONG SBNs

- $SBN_k$: Couple of SBNs with connection.
- $x'$: Sample mean of $SBN_k$.
- $\mu_0$: Hypothesized population mean of UD$_{base-D}$. $\rho N$.
- $\sigma$: Population standard deviation of UD$_{base-D}$. $\rho N$.
- n: Sample size.
- $\alpha$: Acceptance region.

1. $base-D = \sqrt{[SBN_k(x, y, z) - SBN_l(x, y, z)]^2}$
2. For each $\rho$ of UD$_{base-D}$. $\rho N$
3. $z = (x' - \mu_0)/\sigma$\sqrt{n}$
4. if $-\alpha \leq z \leq \alpha$
5. OLI = UD$_{base-D}$. $\rho N$
6. break
7. Return to step 1 for the next $SBN_k$

In step 1, the separation between $SBN_k$ and $SBN_l$ is calculated by using their physical position. In steps 2 and 3, the statistical value $z$ is obtaining respect to each UD$_{base-D}$. $\rho N$ with the fixed $base-D$ obtained in step 1. In step 4, if the value of $z$ is greater/equal than -1.96 and lesser/equal than 1.96, in step 5 OLI is equal to the UD$_{base-D}$. $\rho N$ with the fixed $base-D$ and the estimated $\rho$. The process continues for all SBN$_k$. Once estimated OLI, each SBN transmit a five-tuple (UID, X, Y, Z, OLI), where UID is the unique identifier of the SBN and its physical position at coordinates (X, Y, Z). From this information, an approximation of the RSSI behavior respect to obstacles in each part of the wireless network can be made. For instance, let be $\rho = 0.5$ between the SBN$_3$ and the SBN$_5$, such that SBN$_3$(8,4,3) and SBN$_5$(9,1,8). It can be expressed as SBN$_3$.SBN$_5$ = UD$_{base-D}$. $\rho N$. The same way for the rest of SBN$_kl$ in the WSN.

A non-beacon node can estimate better the distance among it and the heard SBNs with the received OLI from them. Algorithm II shows the process.

ALGORITHM II. ESTIMATING THE DISTANCE AMONG A NON-BEACON AND HEARD SBNS

- $SBN_k$: All heard SBNs by the non-beacon node $N_i$
- $X'$: Sample mean from $SBN_k$.
- $\mu_0$: Hypothesized population mean of UD$_{base-D}$. $\rho N$.
- $\sigma$: Population standard deviation of UD$_{base-D}$. $\rho N$.
- n: Sample size.
- $\alpha$: Acceptance region.
- $N_i$.SBN$_k$ = Estimated distance between $N_i$ and SBN$_k$.

1. $pN$ = $\frac{1}{n} \sum_{i=1}^{n} \rho N$, from all SBN$_k$.
2. For each $base-D$ of UD$_{base-D}$. $\rho N$
3. $z = (x' - \mu_0)/\sigma\sqrt{n}$
4. if -$\alpha \leq z \leq \alpha$
5. $N_i$.SBN$_k$ = $base-D$
6. break
7. Return to step 2 and estimate for the next SBN from SBN$_k$.

In step 1, the average of $pN$ from all SBN$_k$ is computed using their OLI. In steps 2 and 3, the statistical value $z$ is getting respect to UD$_{base-D}$. $\rho N$ with the fixed $pN$ from step 1. If the value of $z$ is greater/equal than -1.96 and lesser/equal than 1.96 in step 4, in step 5 the estimated distance between $N_i$ and SBN$_k$ is equal to the value of $base-D$ from UD$_{base-D}$. $\rho N$ with the fixed $p$ and the estimated $base-D$. With OLI from SBNs non-beacon nodes can infer better the distance between each heard SBN.

IV. Experimental Results

We used the network simulator AvroraZ [17] for evaluating the accuracy of Centroid Localization [5], Triangular Centroid Localization [7] and Weighted Centroid Localization [8] with/without SBNs. Due to TCL and WCL are an extension of Centroid, we set up the position of the beacon nodes similar to the one used in [5]. The beacon nodes were located in a grid way, with 10 meters of separation among them with a coverage range about 18 meters. The first scenario contemplates an area of 1600m$^2$ and the second one considers a volume of 32000m$^3$. 

- $\rho$ = 0.5 between the SBN$_3$ and the SBN$_5$, such that SBN$_3$(8,4,3) and SBN$_5$(9,1,8). It can be expressed as SBN$_3$.SBN$_5$ = UD$_{base-D}$. $\rho N$. The same way for the rest of SBN$_kl$ in the WSN.
The experimental simulations were organized as follows: for each $\rho$ of OLI\textsubscript{coarse} we created a testing group. For each testing group 30 simulations were done. A total of 300 simulations were achieved. For all simulations the non-beacon nodes were established in a random way. For instance, the testing group of $\rho[0.3, 0.39]$, such that the variable $\rho$ was set up at random from 0.3 to 0.39. In order to measure the node localization improvement using and not using SBNs, a simple non-beacon node estimates its position ignoring any OLI, using OLI\textsubscript{coarse} and using OLI\textsubscript{fine}.

The Figure 2 shows the average result for each group of $\rho$ of OLI\textsubscript{coarse}. Notably we can see that the localization error tends to increase when $\rho$ increases, besides we can see the error localization for all LAs is bigger when $\rho[0.9, 0.99]$ than everyone else. The maximum obstacle is 0.99 that is 17.81 people over an occupied area. Nevertheless, if the $\rho$ increases, not necessarily increases the localization error. For instance, the node localization error of WCL when it uses LQI with $\rho[0.3, 0.39]$ is lower than $\rho[0.0, 0.09]$. Similarly, these situations also can be found in TCL. The random position of the non-beacon nodes and density/positions of beacon nodes are also important factors.

![Figure 2. The average error of node localization without SBNs.](image)

The Figure 3 draws the node localization error by using OLI\textsubscript{coarse}. Once again, we can see the tendency of the node localization error to increase. The average error decreased significantly for some groups of $\rho$ and for others group slightly. The localization error for all $\rho$ of each range-based LAs was reduced. For instance, the localization error of TCL by using LQI was reduced in a 7.53% on average and by using RSSI was reduced in a 7.3% on average; the localization error of range-based localization algorithms TCL was reduced in a 12.24% on average. The localization error of OLI (Err) and when they use OLI\textsubscript{coarse} stops in UD\textsubscript{base-D}, $\rho_1$, due to the statistical value $z$ is within the range of the acceptance region. On the other hand, The Algorithm I for estimating OLI\textsubscript{fine} stops in UD\textsubscript{base-D}, $\rho_2$. Thus, OLI\textsubscript{coarse} gets better accuracy than OLI\textsubscript{fine}. However in most cases, OLI\textsubscript{fine} gets better accuracy.

![Figure 3. The average error by using coarse rho.](image)

Summarizing, when SNBs transmit OLI\textsubscript{coarse}, the node localization error of used range-based LAs is improved in a 6.9% on average and OLI\textsubscript{fine} the node localization error is ameliorated in a 12.08% on average. In Table II is shown the localization average error (meters) of tested localization algorithms when they do not use OLI (Err) and when they use OLI (Err (OLI\textsubscript{coarse/fine})).

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Error (m)</th>
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<tbody>
<tr>
<td>TCL</td>
<td>3.5</td>
</tr>
<tr>
<td>WCL (RSSI)</td>
<td>3.2</td>
</tr>
<tr>
<td>WCL (LQI)</td>
<td>3.0</td>
</tr>
<tr>
<td>OLI (RSSI)</td>
<td>2.8</td>
</tr>
<tr>
<td>OLI (LQI)</td>
<td>2.6</td>
</tr>
</tbody>
</table>

The Table II shows the average accuracy of the localization algorithms tested in 2D and 3D environments. Based on these results, we proofed that the inclusion of SBNs into the range-based localization algorithms TCL [7] and WCL [8] can decrease the node localization error up to in an 18%. SBNs can
transmit OLI\textsubscript{fine} for getting more accuracy; of course this indicator demands a little more off-line work than OLI\textsubscript{coarse}.

| TABLE II. COMPARISON OF ACCURACY OF LAS WITH/WITHOUT SBNs |
|-----------------|-----------------|-----------------|
|                | Err  | Err (OLI\textsubscript{coarse}) | Err (OLI\textsubscript{fine}) |
| CL              | 2    | 2                             | 2                             |
| WCL (RSSI)      | 2.41 | 2.27                          | 2.11                          |
| WCL (LQI)       | 3.57 | 3.32                          | 3.15                          |
| TCL (RSSI)      | 0.93 | 0.86                          | 0.81                          |
| TCL (LQI)       | 1.66 | 1.53                          | 1.46                          |

SBNs have been developed in the network simulator AvroraZ [17], therefore the constraints of a real implementation is not possible to analyze in our simulations, however the potential constraints of use of SBN into some localization algorithm may be are: (a) time for generating the database of RSSI/LQI and (b) establish the range acceptance region used in Algorithm I and Algorithm II.

V. CONCLUSION

We have presented Smart Beacon Nodes, which are able to transmit the Obstruction Level Indicator between each couple of them. After extensive simulations using obstacles in random way in 2D and 3D environments, we proved that the inclusion of SBNs into the range-based localization algorithms Triangular Centroid Localization and Weighted Centroid Localization improve their accuracy. Specifically, when SBNs transmit OLI\textsubscript{coarse} LAs improve the node localization in a 6.9% on average and with OLI\textsubscript{fine} they ameliorate the node localization in a 12.08% on average. In additional, the highest improvement was found in TCL, it was 18%.

The central idea is to report the status of the environment to each non-beacon node. In this first approach, we use a generalization of the obstacles (\rho) through the network simulator AvroraZ. However, SBNs can transmit more useful information such as noise, lost packet, transmission delay and the bit error rate, just to name a few. This opens the possibility of develop LAs with these kinds of requirements and extend the SBN for specific or general environments. Actually, we are working in the real implementation of the SBNs outdoors. This is a current research line taken by authors. The results of the ongoing work will be published in a near future.

REFERENCES