Experimental RSSI-based Localization System using Wireless Sensor Networks

J. A. Palazon, Javier Gozalvez
Miguel Sepulcre
Uwicore, Ubiquitous Wireless
Communications Research Laboratory
University Miguel Hernandez of Elche
Avda. Universidad s/n, 03202, Elche, Spain
jpalazon@umh.es, j.gozalvez@umh.es

Gonzalo Prieto
INDRA Sistemas S.A.
C/Anabel Segura, 7, 28108 Madrid, Spain
gprieto@indra.es

Abstract

Many ICT-based future industrial applications will require the localization of machines, devices or even workers. This work presents the experimental implementation, evaluation and optimization of an RSSI-based localization solution using IEEE 802.15.4 wireless sensor networks. The localization accuracy is analysed under different densities of deployed reference nodes. The paper also proposes a simple optimization process that helps improving the localization accuracy.

1. Introduction

The FASyS project (Absolutely Safe and Healthy Factory) [1] was established to develop a new factory model aimed at improving the health and safety of its workers. To this aim, the project is designing new ICT solutions to assist in the detection of risk situations. In particular, the project is working in designing safety prevention systems using low cost and low power consumption IEEE 802.15.4-based Wireless Sensor Networks (WSN) for real-time monitoring. For example, deploying mobile WSN motes at moving vehicles and workers can help detecting possible risks of collisions. To this aim, wireless communications need to be complemented with indoor location information.

Several indoor localization systems using wireless technologies (e.g. RFID, Bluetooth or UWB) have been proposed in the literature [2]. In order to avoid the deployment of different nodes for wireless communications and localization, this study focuses on exploiting IEEE 802.15.4 WSN motes for indoor localization. Localization solutions exploiting wireless signals calculate the position of the target node by estimating the distance between the target node and several reference static nodes. In particular, the distance between a pair of nodes is estimated from the Received Signal Strength (RSS) of exchanged packets. For example, the algorithms proposed in [3] and [4] estimate the distance between two nodes through using the transmitted packets' RSS indicator (RSSI). The proposals apply a non-parametric method known as fingerprinting. This method first performs a calibration stage generating a database with the RSSI levels and distances between each reference node and each possible position in the deployment area. The position of the target node is then estimated by comparing the RSSI measured by this node, and stored values (RSSI and distances) in database. Other proposals, e.g. [5] and [6], use for their localization estimation the knowledge of the propagation model that relates the measured RSSI with the distance between two nodes through a calibration stage. These localization parametric methods are not robust against changes in the transmission or propagation conditions, and require a costly calibration. On the other hand, the proposal in [7] estimates the distance between a target node and the reference nodes using the measured RSSI levels from the packets transmitted by the target node and received at the reference nodes, and a model relating RSSI levels and distances. The RSSI-distance model is parameterized using only reference nodes to avoid the costly calibration during deployment that characterized the other methods. In addition, the technique allows for periodic parameterization updates that increase the robustness against changes in the transmission or propagations conditions. In this context, this paper reports the implementation and experimental evaluation of an RSSI-based indoor localization solution using IEEE 802.15.4 nodes. The conducted study complements related literature that generally lacks from a hardware experimental deployment that evaluates the localization accuracy under different operating conditions, e.g. different node densities.

2. Indoor localization system

Figure 1 shows the architecture of the implemented localization system using distributed IEEE 802.15.4 WSN nodes. The system includes target nodes (attached to workers in the case of the FASYS project), static reference nodes deployed to support the localization, and a coordinator node. The coordinator node is in charge of managing the WSN, and also implements and executes the localization algorithm.

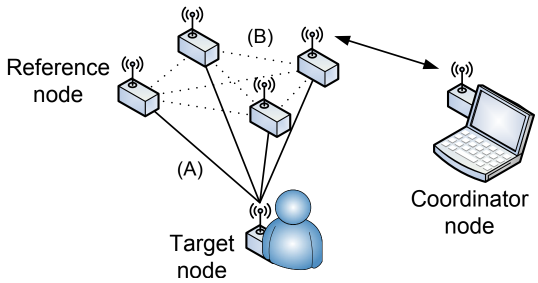

Figure 1. Localization system architecture.

The localization algorithm implemented at the coordinator node executes first a distance estimation phase and then a multilateration one (Figure 2). During the distance estimation phase, the algorithm estimates the distance between a target node and all reference nodes based on the RSSI of the packets received at each reference node from the target node (e.g. link *A* in Figure 1). To calculate the relation between distances and RSSI levels, the dynamic parameterization method proposed in [7] is applied. Based on the estimated distance between the target node and the reference nodes, the position of the target node is calculated using the multilateration method proposed in [8]. The multilateration method has been selected due to its good computational cost-accuracy trade-off [2].

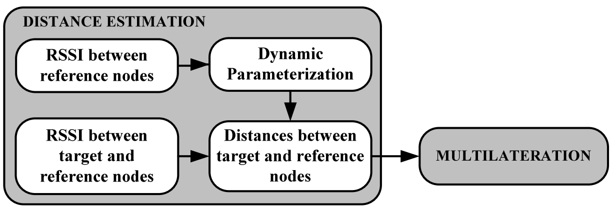

Figure 2. Implemented localization algorithm.

2.1. Distance estimation

The distance between a target node and the reference nodes is estimated using the RSSI level of packets transmitted by the target node and received at each reference node, and the RSSI level-distance model obtained through the parameterization method proposed in [7]. This method dynamically relates RSSI levels and distances using the RSSI levels of packets exchanged between reference nodes (e.g. link *B* in Figure 1). It is important noting that the distance between static reference nodes is known.

Let *N* represent the number of deployed reference nodes. The implemented dynamic parameterization method defines a *N*x*N* matrix *D* with d_{ij} referring to the Euclidean distance between references node *i* and *j*, $\forall$ *i*=1,…,*N* and *j*=1,…,*N*. Similarly, an *N*x*N* matrix *S* is also defined with $RSSI_{ij}$ being equal to the RSSI level of packets transmitted by reference node *j* and received at the reference node *i*. It is important noting that while *D* is constant for a given system deployment, *S* is periodically updated with the objective to dynamically adapt the RSSI-distance relation to possible changes in the transmission or propagation conditions. The relation between *D* and *S* is given by $\log(D) = TS$ [7], where *T* is an *N*x*N* matrix calculated as $T = \log(D)S^T(SS^T)^{-1}$, where S^T is the transpose matrix of *S*. The value of *T* can be calculated using the least squares method [7].

Once the relation between RSSI levels and reference distances is determined, the distance between a target node and the reference nodes can be estimated by collecting the RSSI levels of packets transmitted by the target node and received at each reference node. If $\hat{s}$ is a *N*-dimensional column vector with the RSSI levels of the packets transmitted by the target node and received at each reference node, the distance between the target node and each of the reference nodes can be computed as $\hat{d} = \exp(T\hat{s})$, where $\hat{d}$ is a *N*-dimensional column vector with the distance values.

2.2. Multilateration

The implemented multilateration method estimates the location of a target node $\hat{p} = (x, y, z)$ using the estimated distance to each reference node $\hat{d}$ and the location of each reference node expressed as $p_i = (x_i, y_i, z_i)$, with $1 \le i \le N$. In particular, the location of the target node is computed as the intersection point of the spheres centred at each reference node p_i and with radius equal to the distance to the target node $\hat{d}_i$. In this context, four different and non collinear reference nodes are at least required to provide a target node location. Since the accuracy of the estimated distances can be affected by noise and propagation radio effects (path-loss, shadowing, multi-path, etc.), the spheres might not always intersect at one single point. To solve this problem, the least squares method is applied [8], and the solution can be expressed as:

$$\hat{p} = \frac{1}{2}\left(H^T H\right)^{-1} H^T b \tag{5}$$

where *H* and *b* are expressed as:

$$H = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 & z_2 - z_1 \\ x_3 - x_1 & y_3 - y_1 & z_3 - z_1 \\ \dots & \dots & \dots \\ x_N - x_1 & y_N - y_1 & z_2 - z_1 \end{bmatrix} \quad b = \begin{bmatrix} K_2^2 - K_1^2 - \hat{d}_2^2 + \hat{d}_1^2 \\ K_3^2 - K_1^2 - \hat{d}_3^2 + \hat{d}_1^2 \\ \dots \\ K_N^2 - K_1^2 - \hat{d}_N^2 + \hat{d}_1^2 \end{bmatrix} \tag{6}$$

with $K_i = x_i^2 + y_i^2 + z_i^2$.

3. Experimental evaluation

3.1. Testbed

The WSN deployed to evaluate the localization accuracy consists of MEMSIC IRIS motes working in the 2.4GHz frequency band. These motes were selected due to their reduced cost, low power consumption, and good performance-efficiency trade-off in industrial environments [9]. The IRIS motes implement the IEEE 802.15.4 PHY and MAC layers. The devices are characterised by a maximum data rate of 250 kbps, a -

91dBm receiver sensitivity, and a maximum RF output power of 3dBm. The target and reference nodes are IRIS devices powered by batteries and configured as routers. The coordinator node is an IRIS mote configured as a network coordinator that forwards to a PC through a USB connection the packets received. In the PC, the received information is processed to be used by the localization algorithm implemented using Java on an OSGI (*Open Service Gateway Initiative*) application server.

The omni-directional antennas mounted on the IRIS motes were characterized in an anechoic chamber. The obtained radiation pattern showed gain variations of up to 10dB for different radiation angles. In order to reduce the localization error introduced by these gain variations, the antenna mounted in the IRIS mote has been replaced by Antenova's Titanis 2.4 GHz Swivel SMA antenna whose radiation pattern is more uniform. The Antenova antennas have been connected to the IRIS motes through an adapter cable with loss below 2dB in the 2.4GHz frequency band. Finally, the complete reference and target nodes (IRIS mote, cable and Antenova antenna) used in the experiments have been characterized in an anechoic chamber to verify its gain uniformity for transmission and reception angles. Gain deviations between different measured angles were lower than 3dB for all devices.

3.2. Evaluation scenarios

The performance of the implemented localization algorithm has been evaluated in the two scenarios depicted in Figure 3. In both scenarios, only one target node is deployed at different locations. Each scenario considers a different density of reference nodes: 9 reference nodes are uniformly distributed in an area of $100m^2$ (high node density) and $200m^2$ (low node density) respectively. The target node is located at each test point depicted in Figure 3 for 90 seconds, with its location being computed every second.

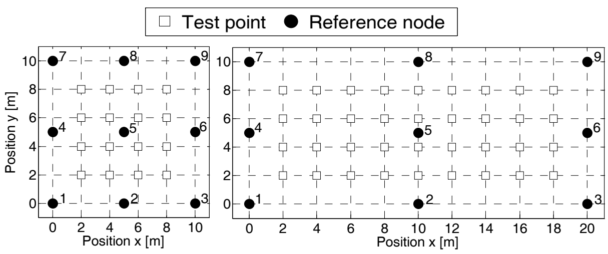

Figure 3. High and low density scenarios.

3.3. Localization performance

Figure 4 shows the cumulative function distribution (CDF) of the localization error for the two scenarios. The localization error is computed as the difference between the position of the target node estimated with the localization algorithm and its real position. The CDFs are obtained using the localization error obtained at all test points depicted in Figure 3, and calculating the position using the information from all reference nodes deployed. Figure 4 shows that the maximum localization error for 90% of the performed estimations performed in the high density scenario is 2.2m; this value decreases to 1.1m when analyzing the 70% of the estimations (a reduction factor of 50%). Under a lower density of reference nodes, the localization error increases to 4.5m and 3.7m for the 90% and 70% of the localization estimations respectively. Whether these accuracy levels are sufficient or not, strongly depends on the target applications.

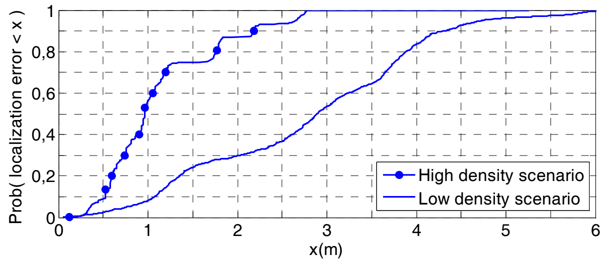

Figure 4. CDF of the localization error.

Figure 5 depicts the average RSSI levels (circles) measured at the reference node 1 from packets transmitted by the other reference nodes in the low density scenario. The figure also shows the 5 and 95 percentiles (vertical bars). The depicted data shows that the average RSSI level of packets transmitted by reference node 7 is 5dB higher than the RSSI levels received from the reference node 2, although both nodes are separated by the same distance from reference node 1. In addition, the figure shows that the reference node 1 measured lower RSSI levels from the farthest reference nodes. It is also important highlighting that the higher the distance between reference nodes, the higher the RSSI variance experienced at the receiver node; a difference between the 5 and 95 percentile equal to 10 and 15dB is experienced for packets transmitted by nodes separated 20 and 22m from the target node respectively (nodes 3, 6 and 9), while only a 5dB variance is perceived for closer nodes.

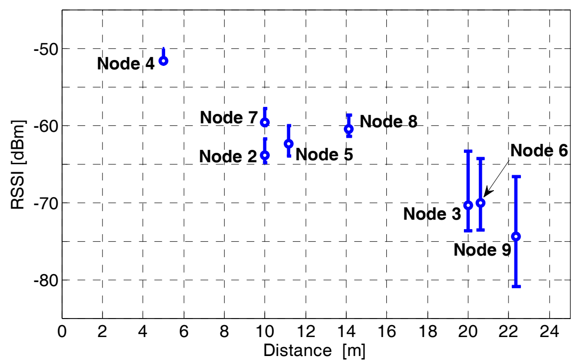

Figure 5. RSSI levels measured at reference node 1 from packets transmitted by the other reference nodes.

3.4. Localization optimization

The previous results have shown that distant reference nodes are characterised by a lower RSSI and higher RSSI variance, which can influence the localization accuracy. To analyse such influence, an optimized version of the localization algorithm has been implemented that only uses the four reference nodes that measure better RSSI levels from the packets transmitted by the target node. It is important noting that the multilateration scheme requires at least information from four nodes to compute the target node's position. Figure 6 compares the CDF of the localization error when considering the original localization algorithm and its optimization. The obtained results show that the optimized algorithm reduces the maximum localization error obtained for 90% of the tests by a 45% factor (from 2.2m to 1.3m) in the case of the high density scenario. On the other hand, the reduction factor for 90% of the tests is just 13% (from 4.4m to 3.7m) in the case of the low density scenario. The performance for this scenario is significantly improved when looking at the 70% of the performed tests: the reduction factor is equal to 50% (from 3.6m to 1.8m), resulting in a localization accuracy similar to that achieved in the high density scenario.

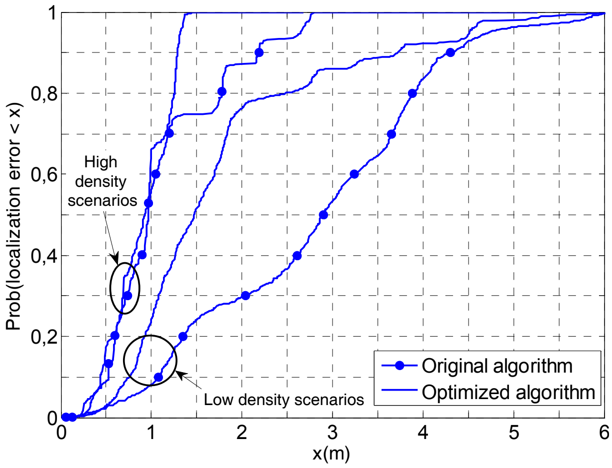

Figure 6. CDF of localization error for the original and optimized algorithms.

Although [7] stated that a high number of reference nodes could improve the localization estimation accuracy, the results presented in this study have experimentally demonstrated that the high RSSI variance for remote reference nodes could decrease the localization accuracy. In this context, the optimum number of reference nodes to be considered in the localization computation needs to be carefully studied in further works and for each deployment scenario.

4. Conclusions

This work presents the experimental implementation and evaluation of an RSSI-based localization solution using IEEE 802.15.4 WSNs. The conducted evaluation has shown that the localization accuracy can be improved through the increase of the density of reference nodes. Whether the localization accuracy is sufficient or not in lower density scenarios strongly depends on the target applications. In any case, the experimental analysis has also shown that the localization accuracy can be significantly improved, in particular for low density scenarios, when considering for the localization computation the information received from the four reference nodes characterised by best RSSI levels.

The authors are currently designing and implementing an additional iterative particle filter to help tracking mobile target nodes.

Acknowledgements

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