Calibrating Location Algorithms for Wireless Sensor Networks based on Signal Strength

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Abstract

A great number of industrial applications could benefit from location aware sensor networks. Many algorithms were proposed, but usually they require specialized hardware for estimating distances between nodes or are computational intensive, thus not being suitable for low-power devices. Every wireless sensor device that use radio channel for communication is capable of measuring the signal strength of received messages. However, when comparing the signal strength with physical distance, although it follows a pattern, there are many factors that interfere in those measurements, thus not being much precise. We show an evaluation of a location algorithm for wireless sensor networks and presents a new calibration in the way that the received signal strength indication is converted to estimated distances, that substantially improved the trustworthiness in position estimates. The results show that adequately adjusted RSSI measurements can be successfully used for localization in Wireless Sensor Networks.

1. Introduction

Location information of sensor nodes can be helpful in a wide range of applications, such as tracking of objects, habitat monitoring, environmental observation and forecasting, battlefield surveillance and enemy tracking. In a food company, for example, sensors could be used to monitor the environment to check if the acceptable conditions are met and a location system would be useful to query localized information. Also, when actuators are available, the nodes' location are fundamental to allow acting only where the action is needed. In a fragile or dangerous goods warehouse, sensors could be deployed in the transportation vehicles, to check if the cargo would not be damaged during transport. With a location system, damaged goods could be easily located, even in such a mobile environment. Moreover, location systems are also useful in the network infrastructure, such as geographic routing [1].

Those applications need a system that provides them some kind of location information. Attaching a GPS (Global Positioning System) device to each sensor node could provide applications with precise location coordinates. The GPS system yields good precision, but has limitations for indoor environments, and is based on a considerable satellite infrastructure, which requires expensive hardware in cost, energy and processing power, as is thus not suitable for low power devices in ad-hoc sensor networks. For this kind of network, the location system should be self-contained (not dependent on a fixed infrastructure), robust to failing nodes and to errors in range measurements. The system should also be implemented considering the restricted power, processing and communication resources in the nodes.

HECOPS (Heuristic Environmental Consideration Over Positioning System) [2] is a distributed location algorithm for Wireless Sensor Networks where every node estimates its own position after interacting with other nodes. Only a limited number of nodes have exact knowledge of their position coordinates. HECOPS establishes a ranking system to determine the reliability of each estimated position, and uses heuristics that are used to reduce the effects of measurement errors, including a scheme to calibrate range measurements by comparing, whenever possible, the estimated distance with the actual distance between a pair of nodes. This work presents an implementation and evaluation of the HECOPS algorithm, and several adaptations to its calibration system. This new calibration system considerably improves the quality of location results, and could be used in any RSSI-based location algorithm.

The main problem of location algorithms that use RSSI as range measurement for distance estimation is its instability noticed in practice, due to signal reflection, diffraction, and scattering [3]. By collecting data in the field and running large-scale simulations of the algorithm, we were able to observe this characteristic and its effect on the behavior of the calibration scheme. We then realized that some alterations in the way that the distances are corrected could considerably improve position estimations reliability, enabling its deployment in real-world applications. In this article we present this new calibration scheme, and compare it with original results of the HECOPS location system.

The rest of this paper is organized as follows: Section 2 describes the HECOPS algorithm. Section 3 presents the infrastructure used for testing, and considerations about the implementation of the algorithm. Section 4 presents our new calibration approach. In Section 5 we present the related works and highlight the differences to our method. Finally, section 6 presents our conclusions.

2. The HECOPS Location Algorithm

The HECOPS location algorithm aims at solving the following problem: given a set of nodes with unknown position coordinates, and a mechanism by which a node can estimate its distance to a few nearby (neighbor) nodes, determine the position coordinates of every node via local node-to-node communication [2]. Hence, some nodes need to have an a priori knowledge of their position based on some global coordinates system. These nodes are called *anchors*. Based on its coordinates, all other nodes will estimate their position. The position information of the anchor nodes can came from GPS devices installed in just a small amount of nodes, pre-established in the source code or by other methods of self establishment of coordinates executed before the location service [4].

An important factor in distributed algorithms of localization is how to estimate distances between pair of nodes directly connected. There are techniques based on time propagation of messages like ToA (Time of Arrival) and TDoA (Time Difference of Arrival), but they need high resolution timers. Other techniques, like AoA (Angle of Arrival) and distance estimation based on optical and ultrasound devices are additional hardware dependent. In order not to depend on any other devices but a radio transceiver, already required for wireless communication, the HECOPS system uses as range measurement the RSSI (Received Signal Strength Indication). The estimated distance is inversely proportional to signal strength received.

The main problem of RSSI is its variation, which is non-uniform in all directions and is easily affected by electromagnetic interferences and physical barriers. These characteristics bring much imprecision into the position estimation system, and must be treated in an efficient way. Figure 1 illustrates the contour of probability of packet reception in relation to distance to a transmitting node *x* [2].

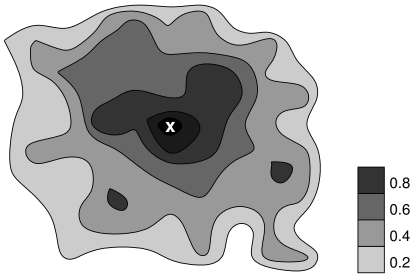

Figure 1. Contour of probability of packet reception from a central node

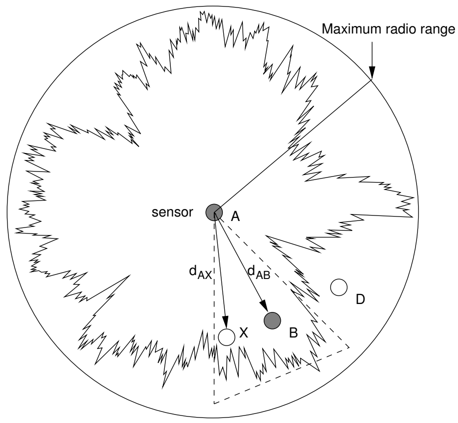

Figure 2. Irregular radio pattern of a sensor and calibration system based on direction.

Previous studies [5] show that, event with the instability of RSSI, its variation is related to the direction of the radio transmission signal. This means that nodes position in the same direction of a transmitter will present similar signal degradation patterns, and similar RSSI readings. Based on that, in HECOPS, the distances to anchor nodes estimated by nodes with unknown position are calibrated by correction factors obtained by other nodes in the same direction. This factor, called *deviation*, is defined by the the actual distance, calculated by nodes that already know their positions, multiplied by the signal strength of a message sent by one of them.

For example, in Figure 2, nodes B and X, by being positioned at the same direction related to A, are supposed to be affected by the same deviation. Considering A and B anchor nodes, the deviation would be given by equation 1, where dev_{AB} is the deviation, d_{AB} the Euclidean distance between A and B, and $RSSI_B$ the RSSI reading of the node B of a message sent by A. Therefore, the estimated distance between A and X would be given by $d_{AX} = \frac{dev_{AB}}{RSSI_X}$. Node D wouldn't be affected by dev_{AB} because it's not in the same direction.

$$dev_{AB} = d_{AB} \times RSSI_B \tag{1}$$

We expect the required anchor proportion be as small as possible, without compromising the results accuracy. For that reason, the HECOPS allows nodes with estimated positions to be chosen as landmarks. In order not to let this characteristic compromise the system's performance, HECOPS uses a heuristic scheme that gives a value to the confidence on location information given by nodes. Each node, when calculating its position, defines a confidence value on the result obtained. This value ranks the nodes that should be chosen by a node that has to estimate its location.

Confidence calculation is based on the confidence value of the nodes chosen as landmarks and on the confidence of the nodes used in distance calibration related to that landmarks. In a scale varying from 0 to 1.0, anchor nodes have maximum confidence on its position, equal to 1.0. The other nodes have confidence limited by 0.8, given by equation 2, where C_x is the confidence on position that is being calculated by a node X, C_i the confidence on each landmark chosen by X (n in total) and C_{ix} the confidence of the node that, together with the node i, have defined the deviation applied to the distance between the nodes i and X, if any (In Figure 2, C_{ix} would be the confidence on node B, considering i the node A).

$$C_x = 0.8 \times \frac{\sum_{i=1}^{n}(C_i \times 0.75 + C_{ix} \times 0.25)}{n} \quad (2)$$

Location information received from anchors is very trustworthy. But, if the distance estimation of that node has been calibrated by another node, the confidence is even greater. For this reason, the weights of 0.75 and 0.25 were attributed for the confidence on a chosen landmark and the confidence of the node used to calibrate the distance between them, respectively. Thus, when a node that has to estimate its position has already chosen its landmarks and have the estimated distances to all of them, it's enough to apply some method to calculate coordinates, like lateration or min-max [6].

In the beginning, only anchor nodes know their positions. They start by broadcasting their identification (ID), coordinates (x,y) and confidence values (Figure 3(a)). The nodes that receive this message store the information together with the RSSI reading. If the receiving node already knows its position, it calculates the distance and deviation between itself and the sending node, and broadcasts this information (Figure 3(b)). This information is in turn stored by the nodes who wish estimate their positions.

ID	
x	y
Confidence	

(a) Position information message.

ID_A	ID_B
$deviation_{AB}$	
$distance_{AB}$	

(b) Deviation information message.

Figure 3. Content of exchanged messages

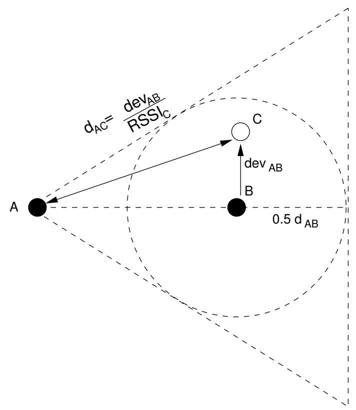

Figure 4. Determining if two nodes are in the same direction, in order to use calibration

When a message with deviation information is received by a node that doesn't know its coordinates, it checks if it's in the same direction than the transmitter, related to the third node described in the message. If it is, it calibrates the RSSI reading of a message sent by that third node with the deviation.

The checking of a node to discover if it's in the same direction of another one related to a sending node is made according to proximity between them. In Figure 4, the node C receives a message from B about the deviation between A and B. So, node C verifies if its distance to node B is lower than the half of the distance to A. In a positive case, node C calibrates the RSSI reading of the last message received from A with the deviation between A and B. When these conditions are met, hereinafter we will refer as the "tri" occurrence.

Position information messages are stored by the nodes that will estimate its coordinates in a list ordered by the confidence value. When the list size reaches 3 it's already possible to execute the position calculation. The 3 nodes of the list with greatest confidence in their positions are chosen as landmarks.

3. Simulations and Evaluation

In order to evaluate the location system implemented in this work, and to allow tweaking of parameters in the location algorithm, RSSI measurements were collected in the field, and stored for offline execution. For this, a wrapper was developed to allow running the same code developed for the sensor platforms with EPOS [7], a deeply-embedded operating system, and in UNIX workstations. Through this wrapper, the same code that would run in a sensor node runs in a thread, and message exchanging is performed through memory copies, using the data collected in the field.

In order to allow this execution scenario, RSSI measurements were collected between every pair of nodes in a 3×3 sensor grid, with nodes $5m$ apart. These measurements served as input for the workstation wrapper. Three nodes from the nine in total were selected as anchors, and three other nodes estimated their positions. Figure 5 illustrates the geographical disposition of the nodes after stabilization of the estimated positions. The arrows indicate the distance between the estimated positions of nodes A, B and C, and the actual position were they were located. This figure shows that the relative disposition of the nodes' estimated position was maintained from the actual position, which encourages the use of this system in applications which require this characteristic, such as geographical routing [1] or location based acquisiotional queries [8].

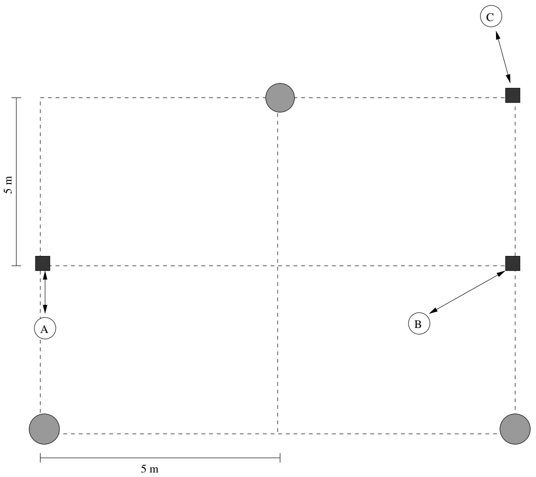

Figure 5. Graphic disposition of the nodes after stabilization

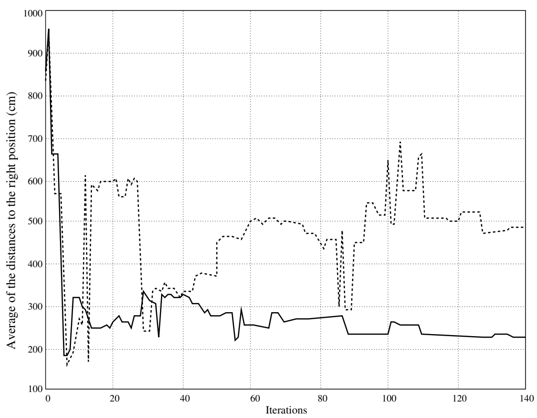

Figure 6. Average distance to the actual positions along iterations

Figure 6 shows the average distance between estimated positions and actual positions along iterations, i.e. the number of times each node has calculated its position. The dotted line shows the behavior of the algorithm in relation to the highly irregular RSSI measurements, which hinder stabilization of the estimated position. In the second curve, a historical average of the RSSI was kept by each node, minimizing the effect of momentary RSSI fluctuations.

The introduction of this historical average may have, as a collateral effect, the invariability of the results along the time, and thus may not be adequate for situations of high mobility, where high variations in RSSI are expected. An alternative for this problem is to keep, in addition to the historical average, an average of the latest measurements and, when the two averages become too far apart, to discard the historical average for the recent one. As the graphic shows, the estimated position stabilizes in the initial iterations, and even if nodes were moving, we would have quick convergence to the new position.

In previously published results [2, 9], we used a simulation model based on the one used to evaluate the Hop-Terrain [10] location algorithm. This model allowed direct comparisons of the two algorithms, but was later found to be oversimplified. When our actual implementation showed considerable improvements through the use of a historical average, we found it necessary to evaluate the influence of calibration in the algorithm through more realistic radio propagation models, as the ones found in the Network Simulator (ns-2) [11].

In our original MatLab model [2], the signal propagation model was in the same scale as the coordinates system, and its variation was considered linear with relation to distance. Medium interference was simulated by adding a random value limited to a percentage of the actual distance. As observed in our field experiments and in recently published research results [3, 12], using a constant relation between distance and RSSI for different distances is too far from reality, thus not being a good model.

In our new simulations, we used the ns-2 "Two Ray Ground" propagation model, which considers node heights (1m above ground in our simulations), and has pass loss exponent (that indicates the rate at which the signal strength attenuates with distance) equal to 4. Signal intensity calculation is given by equation 3, where P_r is the received signal power at distance d from the transmitter, P_t is the transmitted signal power, G_t and G_r are the antenna gains of the transmitter and the receiver respectively and h_t and h_r are the heights of the transmit and receive antennas respectively. In this model, signal intensity is inversely proportional to d^4, and notably non-linear. As in our previous simulations, we used a 10×10 nodes grid. Maximum node range was based on field experiments with Mica2 nodes [13], and equal to 80 meters. In our model, we use the term "connectivity" as the average number of nodes within reach of each node. For different connectivities, we varied the distances between nodes.

$$P_r(d) = \frac{P_t G_t G_r h_t^2 h_r^2}{d^4} \quad (3)$$

We ran different simulations, and came to some unexpected results. In our previous simulations (Figure 7), an

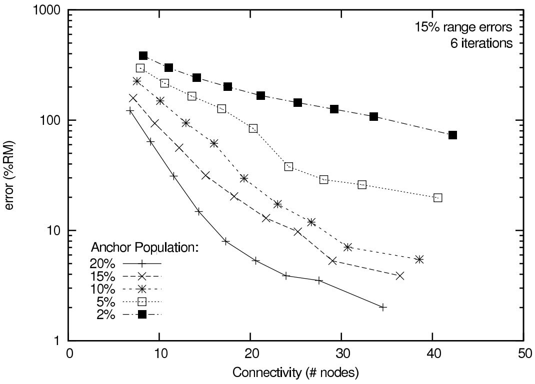

Figure 7. Average Position Error for different anchor populations in the previous published results [2]

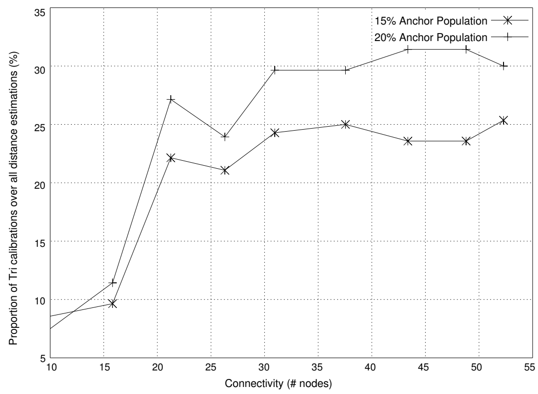

Figure 9. Tri proportion related to all distance estimations varying connectivity

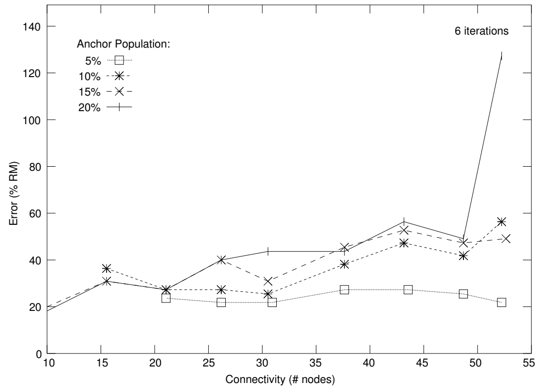

Figure 8. Average Position Error for different anchor populations in our simulations (with a nonlinear signal propagation model)

increase in anchor population considerably decreases location errors. With a nonlinear propagation model and with a large anchor population, the deviation average (used when no "tri" is found), produces an average that does not suit most distance calibrations. This happen because, when there is a high anchor density, there will be several different distances between them, and thus a great variation in deviation, which causes the error in estimated position to grow even when anchor population increases. Figure 8 presents a graph of our new simulations using the same parameters as Figure 7. Positioning error is defined as the ratio between the distance of the actual and estimated position to the maximum reach of the radio signal. In this graph, a smaller anchor population yields smaller error ratios. However, if anchor population is small, only a small quantity of nodes will be able to estimate its position, as many nodes will not be able to connect to any anchors.

In the previous model, deviation average was unnecessary, as the signal intensity was in the same scale as the coordinates system. When no "tri" was found, it was enough to use the RSSI reading as the estimated distance. As this does not occur in practice, we decided to evaluate the impact of introducing the average deviation when "tri" conditions are not met. Figure 9 presents the proportion of "tri" occurrences to the total number of calibrations. The number of "tris" grows with increased connectivity and anchor proportion, but remains close to 30%. Therefore, the number of times when deviation average must be used is approximately 70% of the total number of distance estimations. Enhancements in deviation average calculation methods would probably introduce significant improvement in position estimations errors.

The use of a confidence system, that is, using nodes with estimated positions as anchors, allows the use of a smaller anchor populations, without compromising the ability of nodes to estimate their positions, albeit with smaller precision. However, such a system introduces further error into estimated distances. This error grows when we decrease the landmark eligibility threshold. In our simulations, we ignored the confidence system, in order to avoid interference in other metrics relevant to the current work.

4. New Calibration Approach

Our new simulations and field experiments showed that our calibration approach was incorrect in its disregard of the disproportionality between distance and signal strength values. The method proposed to verify if two nodes are in the same direction is based on the relation between the distance of the estimating node and a nearby anchor, and the distance between this anchor and the node whose direction relationship one wishes to verify. According to Figure 4, if the d_{BC} distance is smaller than $0.5 \times d_{AB}$, C would be considered to be in the same direction as AB, and the dev_{AB} deviation would be applied by node C to the signal intensity of a message received from node A to estimate the distance between A e C. The d_{BC} must be minimal in order for the same signal interference between AB and AC to be considered in the calibration

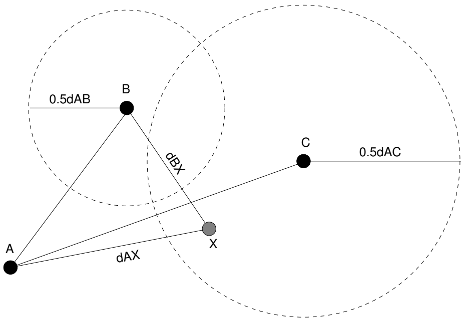

Figure 10. Problem with previously proposed tri

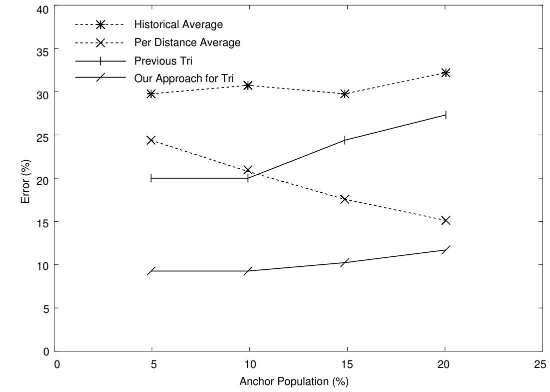

Figure 11. Comparison of distance estimations errors (previous and new approach)

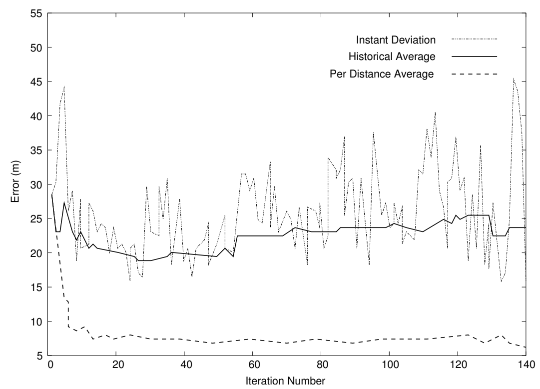

Figure 12. Absolute Error along iterations with different approaches for deviation averages and tri

process. However, when a multiplication factor (0.5) is used, this distance may be wide, when d_{AB} is also wide.

In Figure 10, supposing A, B, and C are anchors, and X wishes to estimate its position, it would verify that its distance to the B node is larger than $0.5 \times d_{AB}$, and would discard the dev_{AB} deviation. It would then verify that $d_{CX} < 0.5 \times d_{AC}$, and would use dev_{AC} in order to calibrate signals from A. Using dev_{AC} in this case would introduce considerable error into the distance estimation between A and X. As signal intensity does not varies linearly to distance, and d_{AB} is closer to d_{AX}, the best deviation factor to be used in this calibration would be dev_{AB}. Although the distance d_{BX} should be considered in order to deal with interference caused by physical barriers or electromagnetic waves, the relation between the d_{AB} and d_{AX} distances should also be considered, in order to allow deviations of a similar distance to be used in the calibration. In addition to the proposed restriction ($d_{BX} < 0.5 d_{AB}$), we also ran simulations that excluded calibration factors when the distance between d_{AX} and d_{AB} was too large, that is, $\frac{|d_{AX} - d_{AB}|}{d_{AB}} > 0.15$, which would exclude dev_{AC} in Figure 10.

Additionally, we've considered RSSI readings as an inversely proportional function to distance, i.e., $P_r(d) = \frac{dev}{d}$, with dev being the deviation. For similar distances, deviation is very similar, independently of the radio signal propagation model. Based on that, we decided to keep an average of deviations according to the distance of the nodes used in its calculation, instead of the average of all deviations. This alteration considerably reduced errors in estimated distances. Alternatively, based on the propagation models *free space* and *ground reflection*, where the pass loss are equal to 2 and 4, respectively [14], the calibration of RSSI could be done by extracting the square or fourth root of $\frac{dev}{RSSI}$.

Figure 11 presents the error obtained in the distance estimations using the previous approach, and the one proposed in this work. Both the "tri" alteration, and the separation of averages by classes of distances considerably reduced errors in estimated distances. Error, in this figure, corresponds to the relation of absolute difference between the estimated distances and the actual distance.

Naturally, the improved distance estimations is reflected in the estimated position. As previously stated, as about 70% distances are estimated through deviation averages, the change in deviation average calculation alone brings considerable improvements. Figure 12 presents errors considering instant deviation variation, historical deviation average and the original "tri" determination, and finally the new deviation by distance and the new "tri". Error is the absolute distance in the coordinates system. In this simulation, one unit corresponds to one meter.

5. Related Works

There is a broad range of proposed location algorithms, varying the range measurement, e.g., ultrasound [15], optical [16], difference time of arrival of radio and sound signals [17], angle of arrival [18] and even algorithms that do not use distance estimation at all [19, 20] (usually coordinates average - centroid - of neighboring anchor nodes is used); and the analytical method for position estimation, e.g., lateration, min-max [6] and iterative multilateration [17]. So, we will focus on calibration and refining methods of similar approaches, i.e., anchor-based algorithms that apply some kind of improvement on distance estimation or on the estimated position.

Savarese et. al. [10] proposed a location system based in two phases: Hop-Terrain, for estimating distances to landmark nodes and so calculating the position through lateration; and Refination, to improve the estimated positions. They do not make assumptions about the range measurement to be used. The Refination algorithm gives confidence values based on properties such quality (anchors or not) and number of directly connected neighbors and normalized residue of the estimated position related to distance of neighbors. Therefore, their approach differ from ours because we, besides giving confidence values on estimated positions, also improve the RSSI estimated distances, yielding a greater precision on position estimation. Considering the error in the same units, that is, the ratio between distance error and radio range, using our calibration system, we got about 10% of error with 15% of anchor population and connectivity of 30 nodes in contrast to about 25% of error with anchor population between 10% and 20% and connectivity of 25 nodes reported by them. Note that no propagation model is used in their simulations, but an artificially random error limited to 5% of the radio range for those results.

Savvides et. al. [6] proposed the "N-hop Multilateration Primitive", for estimating and refining initial rough estimations based on selected neighbors. That selection is made in a way that the system of equations have a unique solution. Afterwards, the bounding box method is used to find the first estimates. Then, the refining process is made by applying the Kalman Filter, a method whose purpose is to reduce the global residue considering the estimated positions and distance estimations. They present a centralized solution, that is computation-intensive that wouldn't fit in low processing power nodes and an alternative distributed solution, that considers only local and neighbor information. The main difference in the refining process is that we act on the distance estimation, the main source of errors for RSSI-based location algorithms. Our refining in position estimations is similar, although we use least squares method and do not consider multihop estimations. Other works also deal with corrections on estimated position, accepting the raw range measurement data [21].

An approach based on signal strength and that improves the estimated distances is the RADAR system [22]. This work focuses on indoor environments, such localizing people using PDAs inside a building. The measurements are made in two phases. The first phase intends to create maps of the signal strengths inside the deployment environment by sampling the signal transmissions to fixed base stations. In the second phase the users' locations can be estimated by observing the signal from their stations and matching with the measurements from the first phase. Although good results are achieved, as the signal propagation at the specif deployment environment is considered, their system wouldn't be suitable for dynamic environments, where signal propagation changes along the time, even by mobility or intense interference (that is usual in low frequency radios).

6. Conclusion

This paper described and evaluated the HECOPS location algorithm for Wireless Sensor Networks under extensive simulations, using different models and assumptions than our previous work. We observed that, even with the restrictions of low cost and low computational power devices, it is possible to use an RSSI-based location algorithm, as long as some adaptations for performance and accuracy are introduced in the implementation of the location system for real world deployment.

We have proposed a calibration approach that brought great improvements to the results and could be used to any anchor and RSSI-based location algorithm. This calibration method does not depend on nonlinear propagation models and we've shown that it has a good performance in such environments.

Although RSSI measurements have been discouraged as a reliable distance estimation tool for wireless networks, due to its instability and susceptibleness to noise and interference, we found that with calibration, cooperative position exchanging, and heuristics, we may obtain good location results based on such measurements without the need for additional hardware.

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