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Relational position location in ad-hoc networks

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ABSTRACT

Position location usually relies on direct observation to/from conventional landmarks with known positions from/to a Node of Interest (NOI). Nonetheless, in an Ad-Hoc Wireless Sensor Network (AHWSN), nodes are often unable to establish a direct connection with the available Access Points (APs). In such a scenario, neighboring nodes may supply cooperative information to enable inference of the location of a given NOI in a network. In this paper we examine the feasibility of relational techniques in multihop environments to estimate position location. Two novel position estimation techniques are presented: the Relative Proximity Algorithm (RPA) and the Enhanced Relative Proximity Algorithm (ERPA). RPA and ERPA can operate as range-based or as range-free techniques, which makes them both attractive and flexible solutions for position estimation in AHWSNs. The performance of these techniques is characterized and found to be related to the number of cooperating nodes, the number of APs available in the network, and the presence of measurement noise. RPA and ERPA are also compared to several known position location methods reported in the literature, and it is shown that they achieve adequate location estimation accuracy with some advantages in terms of the number of access points required and network traffic overhead.

1. Introduction

Nodes in ad hoc wireless networks are generally equipped with sensors, which gather information about specific events of interest associated to a given location [1]. In addition, nodes are capable of processing and transmitting such information. In order to take full advantage of sensed data, the determination of the position location information of the nodes in the network is essential [2]. This is because they may not occupy a permanent location as they might be subject to intentional or unintentional motion [3]. Therefore, position location algorithms are demanded for a wide variety of applications, such as factory logistics, warehousing, real time surveillance, environmental control and monitoring, among others [4].

Location is always described in relation to a coordinate referential system defined by known conventional landmarks [5]. Nonetheless, direct observation from a given node to known landmarks is unlikely in an Ad-Hoc Wireless Sensor Network (AHWSN) because of limitations in the transmission range of nodes and adverse propagation conditions. Therefore, in AHWSNs, conventional landmarks or Access Points (APs) are reached through the concatenation of consecutive links, defining a multi-hop transmission path. In such a scenario where APs are unable to establish a single-hop connection with most network nodes (thus providing them with only limited reliable information), location must be inferred from the context of several descriptors. These descriptors are often related to population features that characterize the neighborhood of a nearby node [6,7]. Hence, location determination of a node becomes a task that involves the cooperation from several nodes in the network. Therefore, cooperative

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position location methods have been suggested over the last decade for these type of scenarios [5,8].

Although several cooperative location techniques have been recently proposed [9,10], many of them require a preprocessing stage in addition to the location estimation stage. This requirement may have adverse effects on their performance. For instance, the preprocessing stage significantly augments the number of information packets transmitted across the network, increasing traffic overhead. Furthermore, several cooperative location methods present low estimation accuracy even with a large number of APs deployed throughout the network (which also increases the implementation cost of the system) [3]. Therefore, it is necessary to develop low-cost, accurate, and efficient cooperative location algorithms.

In this paper, we examine the applicability of simple cooperative relational information for position location in multihop environments. Different proximity measurements (i.e., range-based and range-free) are suggested to be used in the determination of the position of a node. Position location estimation is carried out employing two novel methods, the Relative Proximity Algorithm (RPA) and the Enhanced Relative Proximity Algorithm (ERPA), where in principle the estimation is based on the amount of neighboring nodes surrounding the Node of Interest (NOI) to be located. Performance results of both techniques are presented for several scenarios. Nevertheless, position location estimation may be affected by measuring errors and even by routing techniques [11]. Therefore, the effect of composed proximity error on relational position location is analyzed. In addition, in order to further highlight their advantages, the performance of the proposed methods is compared to that of other position location techniques reported in the literature in scenarios where measurement noise, node density, and available APs are varied.

The remainder of the paper is organized as follows: Section 2 provides a brief summary of position location methods for multihop networks. Section 3 describes RPA, a novel, basic and simple position location technique based on the concept of proximity. In Section 4 ERPA, an enhanced version of the RPA, is presented. ERPA provides important performance advantages over previously published position location systems. Such a comparison is presented in Section 5, where both proposed algorithms are evaluated through computational modeling. Finally, Section 6 contains the conclusions of this work.

2. Related work

The Global Positioning System (GPS) can be regarded as the most widely employed position location system in the world [12]. Nonetheless, in some particular environments (e.g., AHWSNs), GPS presents important drawbacks, for instance: deployment cost, service availability, and estimation accuracy [13–15]. Therefore, cooperative and collaborative algorithms have been developed over the past decade to solve the position location estimation problem in AHWSNs [9,16–18]. In this section, we briefly review some of the best-known and more recent localization schemes for multihop networks available in the literature, although the review is not exhaustive, it does present important algorithms from the point of view of their relation to the methods proposed in this paper. In Section 5, some of those algorithms will serve as a benchmark for the performance evaluation of RPA and ERPA.

In [19], the DV-Hop method was presented, which is perhaps the simplest available approach to follow in order to estimate the position of a NOI. It consists of two stages: a preprocessing stage and an estimation stage. In the preprocessing stage, employing shortest path routing, every node (including the APs) calculates its distance in hops (or links) to every AP available in the network. Since APs are assumed to know their own positions, they will have the information of the Euclidian distance between themselves. Therefore, employing the Euclidian distance and the hop count, APs are able to estimate the "average hop-length" factor, which is broadcasted to the network. Then, in the estimation stage, the NOI estimates its distance to each AP by multiplying the hop count in the path joining it to each AP times the average hop-length factor. Finally, a simple triangulation process can be employed to estimate the position location of the NOI. Recently, in [20], the DV-Hop estimation accuracy was enhanced through the use of a linear programming approach for minimization of the hop-length factor. Their results suggest an estimation accuracy improvement of roughly 20% (in comparison with the standard DV-Hop approach) for high node density scenarios. Nonetheless, its estimation accuracy cannot be further improved, not even increasing the number of APs or the communication range of the nodes.

One of the most important issues in every positioning or localization algorithm is the number of reference nodes that are needed to obtain accurate results. In [21] the localization problem is presented as an optimization formulation where the number of reference nodes is to be minimized. The authors use greedy algorithms and trilateration methods in their formulation. In addition to the required amount of available reference nodes, another important issue is the deployment (distribution) of the reference nodes in AHWSNs. In [22], it is recommended that the reference nodes be deployed in a circle that surrounds the entire sensor network as it minimizes position estimation error. The paper considers the case of very-large-areas AHWSNs, such as those employed for environment monitoring, surveillance, and tracking applications. Furthermore, Ref. [22] also presents the most important proposed improvements for the original DV-Hop algorithm, which is used as a reference algorithm for comparison purposes in the results. The localization algorithm proposed in [22] is named Hybrid DV-Hop (HDV-HOP) because it exploits DV-Hop advantages and the minimization of energy consumption, flooding of messages and number of reference nodes needed for localization. Moreover, the authors had also shown that depending on the scenario and the algorithm considered, an increased number of reference nodes does not always leads to a smaller localization error.

Also in [19], the authors presented the range-based version of DV-Hop, which was called DV-Distance. This alternative follows the same approach described in the previous paragraph with just slight changes in the process.

In the preprocessing stage, nodes do not calculate their distance in hops to each AP available in the network, instead, the hop-length of each link in the multihop route connecting a node with an AP is estimated employing range-based measurements (received signal strength, time of arrival, etc.). Finally, the length of the multihop route is calculated through the addition of the individual hop-lengths that form the path joining the node and the AP. Multihop routes in AHWSNs are commonly zigzag shaped, and therefore, the addition of the individual hop lengths leads to an overestimation of the route length. Thus, in DV-Distance a correction factor is calculated to mitigate the adverse effect of route length overestimation in position location estimation.

Another cooperative position location algorithm was presented in [19]. This approach is known as the Euclidean propagation method. In this scheme, it is the Euclidean distance between nodes what is shared between neighbors. For instance, let us assume that nodes B and C are able to establish a single hop connection to an AP and also between themselves. In addition, there exists another node, A, that is unable to establish a single hop connection to the AP. However, node A can establish a single hop connection to nodes B and C. Node A measures its distance to nodes B and C, and nodes B and C share their distance measurements to the AP and also the distance measurement between themselves with node A. This information then allows node A to calculate its Euclidean distance to the AP. According to [23], this position location technique can provide very accurate position estimates of a NOI in dense networks (at least 12 neighbors per node).

From the methods mentioned above, it is clear that DV-Hop, being range-free, is the least expensive solution. In this same direction, the Approximate Point in Triangle (APIT) algorithm was developed [14]. In APIT, a NOI communicates with the available APs surrounding it. For APIT to estimate the position location of the NOI, it is required that at least three APs are available within a single-hop from the NOI. Each group of three APs defines a triangular region. Then, the position location estimate of the NOI is obtained by calculating the centroid of the intersection of the triangular regions enclosing it. Therefore, in order to provide accurate position estimations with APIT, it is essential to have a considerably large amount of APs deployed across the network defining several triangular regions. Unfortunately, increasing the number of APs in the network increases the implementation cost of APIT.

In [17], a collaborative localization is introduced, where nodes are of three kinds, the normal node (usually the node of interest is a normal node), the anchor or reference node, and the beacon node. The localization of normal nodes is carried out by considering combined range-free and range-based localization schemes. Normal nodes and beacon nodes are deployed randomly, although it is preferred if at least a beacon node is within the intersection of the coverage areas of two reference nodes, which limits the random deployment the authors proposed. The estimated distance based on the received signal strength is based on the classical simplified power received model which is dependent on the path loss exponent and a log-normal random variable. The localization operation is performed with at most three beacon nodes, and reference nodes only provide information of angles toward the normal nodes. This algorithm requires certain deployment of nodes and the so-called reference nodes only provide information which can be dynamic (not considered in [17]) and changing. Claiming that at most three beacons are needed for localization is not the same as saying that only three reference nodes are needed. This is because reference nodes also play an important role and hence, we could say that, at least four nodes are involved in any localization. Besides, this algorithm requires a high number of beacon nodes to have good performance (an average of 4 m of error for 60 or more beacon nodes). The paper shows comparisons against Concentric Anchor Beacon (CAB) and APIT, outperforming both methods.

Multi-Dimensional Scaling (MDS) algorithm presented in [13] estimates the position of blindfolded nodes following three steps. First a distance matrix is formed containing distance measurements between all pairs of nodes in the network. Then singular value decomposition (SVD) is employed to produce the first approximation of the network map. Finally, information from anchor nodes is employed to optimize this map through rotations and scalings.

In [18], authors present a cooperative algorithm based on received signal strength (RSS) to localize sensor nodes. The method assumes *a priori* knowledge of the RSS Indication (RSSI) patterns of any pair of nodes in the network (nodes are either sensors or reference nodes) at any distance. Some of the sensor nodes to be localized will be within the areas with specific RSSI levels, and the localization is more accurate as more reference nodes cover the node of interest. When multiple reference nodes cover the node of interest with their signal, then they collaborate calculating an estimate of the positions. The reference nodes transmit a series of beacon signals to the node of interest and the RSSI patterns measured during this procedure, are matched to those known. The method proposed has better performance than Multi-Dimensional Scaling (MDS) algorithm with different weighting factors including Maximum Likelihood Estimation (MLE). In contrast, the method we propose, does not need of a pre-processing stage which is equivalent to the need of knowing *a priori* the RSSI maps. Also, if the environment changes, which regularly does, the RSSI maps would have to be obtained once again, which is not desirable in an AHWSN.

As discussed, most of these techniques require a pre-processing stage that increases power overhead in the network, and they estimate the location of the nodes at the expense of great computational effort [3]. In the next section, we introduce a position location technique that uses information from the surrounding environment to determine distances and relative positions. The algorithm is based on knowing the number of neighbors surrounding a NOI and their respective closeness to available APs, hence needing low computational processing capabilities.

3. Relative Proximity Algorithm (RPA)

In this section, the Relative Proximity Algorithm is introduced by first analyzing a simple scenario of two

APs, to be extended to the three-AP scenario as well. In both scenarios, nodes in the network are assumed to be able to distinguish or identify those nodes within their coverage region, so that they can share information regarding reachability of APs. Thus, a NOI in an AHWSN has specific knowledge about its neighboring nodes.

The Relative Proximity Algorithm assumes that nodes in the network are able to distinguish or identify those nodes that are within their coverage region, so that they can share information regarding reachability of APs. It is assumed that some of the nodes $\mathbf{n}_s$ surrounding the NOI know the value of a parameter called proximity index, $\delta_{s,i}$, which is related to the distance between the node and a given AP_i. Thus, a NOI $\mathbf{n}_0$ to be located will have associated a non-empty R-neighborhood or R-ball, $\mathbf{B}_R(\mathbf{n}_0)$, defined as the set of all the nodes reachable from $\mathbf{n}_0$ in one hop within a coverage region of radius R, which is set by the transmitting power and the sensitivity of the nodes in the neighborhood. In other words, node $\mathbf{n}_s \in \mathbf{B}_R(\mathbf{n}_0)$, if and only if $|\mathbf{n}_s - \mathbf{n}_0| \leqslant R$, where $|\mathbf{n}_s - \mathbf{n}_0|$ represents the distance between nodes $\mathbf{n}_0$ and $\mathbf{n}_s$. The area covered by this R-neighborhood is denoted as A_R. In a two-dimensional scenario, and for an AHWSN with a homogeneous propagation environment, the area A_R covered by this R-neighborhood is a circle.

In reference to the proximity indexes, it must be noted that the accuracy these proximity indexes have, will depend on the deployed technologies for proximity estimation (e.g., range-based or range-free), as well as on the accuracy of such technologies and the prevailing propagation conditions. As an example, in the case of multihop connections the proximity index may refer to the number of required links or hops needed by a node $\mathbf{n}_s$ to reach an access point [24]. Thus, under a minimal distance routing protocol, the proximity index is related to the node-to-access point distance.

In order to assess how these proximity indexes and the R-neighborhood work within our position location algorithm RPA, let us consider a basic scenario with two access points, AP_i and AP_j. Let N be the total number of nodes reachable by the NOI in one hop, i.e., these nodes are within the R-neighborhood defined by the ball $\mathbf{B}_R(\mathbf{n}_0)$ surrounding the NOI. Note that this number N can be split into two terms, N_i and N_j according to a vicinity criterion of the form $\delta_{s,i} \leqslant \delta_{s,j}$, for all nodes $\mathbf{n}_s \in \mathbf{B}_R(\mathbf{n}_0)$. In other words, $N = N_i + N_j$, where N_i stands for the number of nodes with proximity indexes that indicate they are closer to AP_i than to AP_j, similarly for N_j. In this first approach, we can assume that no true distance measurements are available. Nevertheless, the inequality of the proximity indexes $\delta_{s,i} \leqslant \delta_{s,j}$ can be based on coarse observations, as mentioned before, when using $\delta_{s,i}$ as the number of hops or links in the path joining the neighboring node $\mathbf{n}_s$ and a given access point.

From the information of the number of neighboring nodes, N_i and N_j, obtained from the R-neighborhood through the use of the proximity indexes, the proposed method gets the proportions of the nodes in the vicinity of the NOI to indicate proximity to the access points. In other words, in a homogeneous node density scenario, by considering the proportion $N_i/(N_i + N_j)$ the algorithm has an indicator of the relative proximity of the NOI to the access point AP_i. Similarly, the proportion $N_j/(N_i + N_j)$ is considered for the relative proximity to access point AP_j. Note that this would mean that for a homogeneous node density scenario in an AH-WSN, when $N_i = N_j$, the NOI $\mathbf{n}_0$ is expected to be equidistant to both APs. And since the NOI does not necessarily lie on the line segment $AP_i \leftrightarrow AP_j$ joining access points AP_i and AP_j, it will be assumed to be on the perpendicular line $AP_i \perp AP_j$ evenly bisecting the segment connecting the two access points (see Fig. 1).

When the proportion of nodes closer to an access point determines that there is an unbalance, e.g., $N_i \geqslant N_j$, this will be consistent with a drift Δ_{ij} of the NOI $\mathbf{n}_0$ toward the access point for which such proportion is larger, i.e., AP_i. Under these conditions, the NOI will be assumed to be on a line λ_{ij} perpendicular to the line segment $AP_i \leftrightarrow AP_j$ that is drifted toward AP_i, see Fig. 1. We can extend this idea to the more general scenario where three access points are present. Thus, the same argument as that just described, can be applied in the presence of a third access point, AP_k.

The relative proximity algorithm is based on the assumption of a homogeneous scenario where nodes are uniformly spread in the coverage area A_R, and the number of nodes N in such area A_R is distributed according to a Poisson random variable, i.e., $(\lambda A_R)^N e^{-\lambda A_R}/N!$, where λ is the node density parameter. It can be seen that for a given number N, the maximum probability occurs for $\lambda A_R = N$ [5]. Note that the total number of nodes, N, within the ball $\mathbf{B}_R(\mathbf{n}_0)$ surrounding the NOI is known, as it is the number of nodes reachable by $\mathbf{n}_0$ in one hop.

Now, defining the disjoint areas A_i and A_j such that they form a partition of area A_R of $\mathbf{B}_R(\mathbf{n}_0)$. Then, nodes in areas A_i or A_j are those nodes closer to access point AP_i or AP_j, respectively. Assuming independence of occurrences of nodes in A_i and A_j, the total number of nodes in area A_R, has pdf given by

$$\begin{aligned} P\{N_{A_R} = N\} &= P\{N_{A_i} = N_i, N_{A_j} = N_j\} \\ &= \frac{(\lambda A_i)^{N_i}[\lambda(A_R - A_i)]^{N_j} e^{-\lambda A_R}}{N_i! N_j!}, \end{aligned} \quad (1)$$

and a maximum a posteriori approach leads to $A_i = N_i A_R/N$. This is, the size of area A_i is a proportion of the total area A_R, where the proportion is given by the number of nodes in A_i regardless of node density. Recall that for an AHWSN with a homogeneous propagation environment, area A_R becomes a circle, and the proportion $N_i/(N_i + N_j)$ allows to place the NOI on the line λ_{ij} parallel to $AP_i \perp AP_j$. Note that such line λ_{ij} is drifted Δ_{ij} length units toward AP_i as a function of the proportion of nodes closer to AP_i than to AP_j as shown in the expression

$$2\pi R^2 \frac{N_i}{N_i + N_j} = R^2 \cos^{-1}\left(\frac{\Delta_{ij}}{R}\right) - \Delta_{ij}\sqrt{R^2 - \Delta_{ij}^2}. \quad (2)$$

Now, considering a third access point AP_k, the perpendicular lines $AP_i \perp AP_j$ and $AP_j \perp AP_k$ are known, and after finding drifts Δ_{ki} and Δ_{jk}, the drifted lines λ_{ki} and λ_{jk} can be defined and the NOI will be said to be at the centroid of the area defined by the intersections of drifted lines λ_{ij}, λ_{jk}, and λ_{ki}.

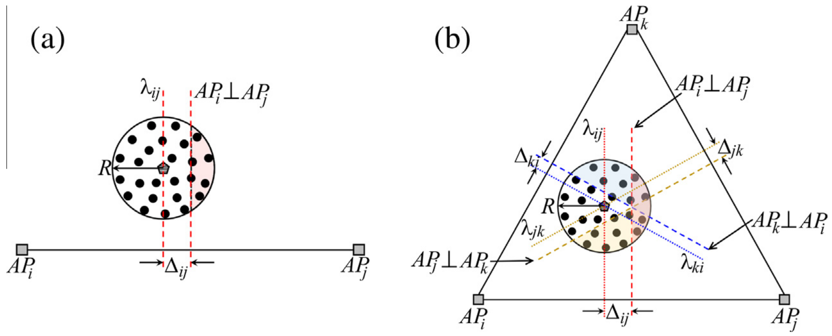

Fig. 1. Typical neighborhood scenario for RPA location estimation (NOI is at the center of the circle); (a) basic scenario with 2 APs and (b) position location with 3 APs.

Note that in the case of an uneven distribution of nodes, and in the absence of a node concentration clue, a fairly uniform distribution can be assumed in the vicinity of the NOI. This is, although node concentration can differ widely in the service area, variations in each coverage area are small. Therefore the point where the number of nodes associated to AP_j distributes equally as the number of nodes associated to AP_i shifts to the point where areas A_i and A_j satisfy the condition

$$\frac{(\lambda_j A_j)^{N_j}}{N_j!}\exp\{-\lambda_j A_j\} = \frac{(\lambda_i A_i)^{N_j}}{N_i!}\exp\{-\lambda_i A_i\}. \tag{3}$$

This is, for $N_i = N_j$, $\lambda_j A_j = \lambda_i A_i$ and $A_j + A_i = A$. Note that in the case of $\lambda_j = \lambda_i$, $A_j = A_i$, leading to $\Delta_{ij} = 0$. For the sake of simplicity, we consider in the rest of this paper that nodes distribute with a uniform node density λ across the service area.

Performance results for this technique, which are presented in Section 5, demonstrate that this approach provides acceptable position estimation accuracy where estimation errors decrease as the number of neighboring nodes within the R-neighborhood increases. Nonetheless, in the next section we present an enhanced version that decreases location estimation error for most scenarios when high density of nodes is present in the network.

4. Enhanced Relative Proximity Algorithm (ERPA)

In this section, we present an improvement to the RPA introduced in the previous section that enhances performance of the algorithm. The improvement is characterized by changing the use of perpendicular lines in RPA by the use of hyperbolas to locate the NOI. ERPA uses the same kind of proximity indexes as RPA, but the set of indexes is treated differently to generate the hyperbolas. Thus, a different approach to relative proximity location estimation can be developed from the same proximity indexes described previously, i.e., $(\delta_{s,i}, \delta_{s,j}, \delta_{s,k})$ for the scenario with three access points (see Fig. 2). The accuracy of these proximity indexes varies depending on the observation technique. For instance, in a multihop scenario with a route linking node $\mathbf{n}_s$ to AP_i, the proximity index $\delta_{s,i}$ can be obtained from the addition of consecutive hop length estimates in the path linking the nodes. These hop lengths can be estimated from perceived field strengths or propagation delay of signals traveling between consecutive nodes. Assuming that routing methods select the shortest path, and in the absence of time measuring or field intensity measuring capabilities, the number of hops will provide an indicator of the proximity of a node to the access point.

Now, considering a homogeneous node density scenario in the network, and regardless of the way that proximity indexes are obtained, when the equality $\delta_{s,i} = \delta_{s,j}$ is satisfied, we expect node $\mathbf{n}_s$ to be equidistant to access points AP_i and AP_j, this allows to define an orthogonal line $AP_i \perp AP_j$ evenly bisecting the segment connecting the APs where all points in the line are equidistant to the access points AP_i and AP_j as explained in the previous section (see Fig. 1).

When the proximity indexes $\delta_{s,i}$ and $\delta_{s,j}$ differ, we still consider that the node $\mathbf{n}_0$ is a typical representative of its neighbors. In such a scenario, the proximity index $\delta_{0,i}$ from the NOI $\mathbf{n}_0$ to AP_i can be taken as the average of all the proximity indexes of all the neighboring nodes $\mathbf{n}_s \in \mathbf{B}_R(\mathbf{n}_0)$ to the access point AP_i. This is, the proximity index $\delta_{0,i}$ is given by

$$\delta_{0,i} = \frac{1}{N}\sum_{s=1}^{N}\delta_{s,i}. \tag{4}$$

Now, given the mean proximity indexes $\delta_{0,i}$ and $\delta_{0,j}$ to access points AP_i and AP_j, respectively, the node $\mathbf{n}_0$ is meant to be on the feasible location locus that is described by the hyperbola H_{ij} locus as the set of points that satisfy the expression

$$\frac{|\mathbf{n}_0 - AP_i|}{|\mathbf{n}_0 - AP_j|} = \frac{\delta_{0,i}}{\delta_{0,j}} = \zeta_{ij}. \tag{5}$$

When a third access point AP_k is used in the algorithm, the NOI feasibility region can be reduced to the intersection of hyperbolas H_{ij} and H_{ki}, and in order to cope with the randomness of the proximity estimates, $\delta_{0,i}$, $\delta_{0,j}$, $\delta_{0,k}$, the hyperbola intersections $H_{jk} \cap H_{ki}$ and $H_{jk} \cap H_{ij}$ are also considered, and $\mathbf{n}_0$ is assumed to be at the centroid of these intersections. Although this suggests a merely algebraic process average, errors arise as the nodes $\mathbf{n}_s$ occupy random locations within the R-neighborhood or R-ball $\mathbf{B}_R(\mathbf{n}_0)$. Also, distance estimates $\delta_{s,i}$ exhibit uncertainty as they are subject to routing impairments when $\delta_{s,i}$ includes the number of hops, or subject to propagation errors when

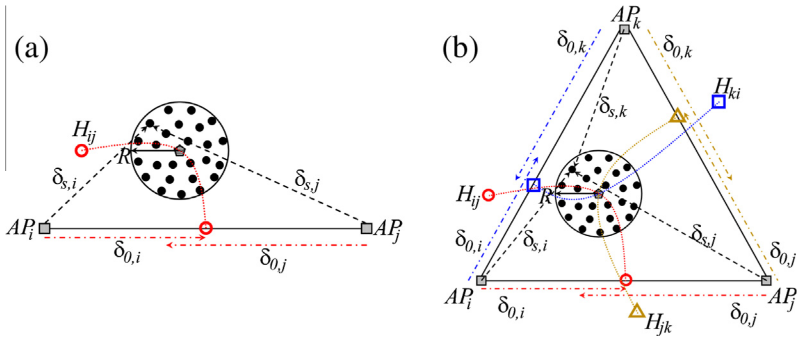

Fig. 2. Hyperbola locus for feasible location in ERPA. Proximity indexes represent distance measurements. NOI is at the center of the circle; (a) basic scenario with 2 APs and (b) position location with 3 APs.

field intensity or delay measurements are involved. Similarly, and as previously discussed in Section 3, the number of nodes N in the ball is a Poisson distributed number. In the following section we report numerical results on the performance of the algorithm, characterizing the effects of measurement errors, number of neighbors per node, and network node density on estimation accuracy for different scenarios.

5. Results

In order to assess the estimation accuracy of the proposed techniques, several simulations were carried out. For each simulation, several (three or more) APs with known locations were assumed to be available in the network. These APs were positioned on a plane in such a way that a convex polygon with side length L was defined. Nodes were randomly generated with a uniform distribution. Network node density was adjusted in order to provide the NOI with a specific number of neighbors. Then, from all the nodes available in the network, one was randomly selected to be the NOI. Simulation scenarios are characterized by the ratio $\sigma = R/L$ in percentage ($\sigma \geqslant 100\%$ indicates a single-hop scenario, whereas $\sigma < 100\%$ indicates a multihop scenario). Increasing σ is the same as increasing the size of the R-neighborhood or R-ball, $\mathbf{B}_R(\mathbf{n}_0)$, hence, increasing the number of nodes surrounding the NOI. Position estimation error is given by the difference between the actual position of the NOI and the estimate given by the algorithms. A common practice in the literature is to report algorithm performance results in terms of error normalized with respect to the node coverage radius. Therefore, in this paper we report normalized root mean square error (RMSE).

Fig. 3 presents normalized RMSE curves for DV-Hop, RPA, and ERPA under different scenarios. Fig. 3a compares the performance of RPA (when the location is at the intersection of straight lines) and ERPA (when the location is at the intersection of hyperbola loci) versus the number of neighbors for multihop noise-free scenarios (i.e., where neighboring nodes know their precise distances to each AP in the network). On the other hand, Fig. 3b compares the performance of the three position location algorithms as a function of σ and the number of available APs in the network.

From Fig. 3a, it can be observed how localization accuracy improves for both techniques as the number of neighboring nodes grows. However, this improvement is more significant for ERPA than for RPA. The reason behind this behavior is that when the NOI knows its actual distance to each AP in the network, ERPA allows it to estimate its true position. On the other hand, RPA can only estimate the exact location of the NOI when it lies in the straight line that connects two given APs. If the NOI is displaced upwards or downwards from this line, the estimation of the drift, Δ_{ij}, will be less accurate. Thus, for RPA, under most scenarios it is impossible to estimate the exact location of the NOI even in the presence of exact distance measurements. Therefore, an increase of one node in the neighborhood has a more significant positive effect in the estimation accuracy of ERPA than it does in that of RPA. Moreover, results verify that ERPA renders in better performance than RPA for most scenarios. Nonetheless, for large values of σ and low number of neighboring nodes (i.e., approaching single-hop scenario category) RPA presents better estimation accuracy than ERPA. In addition, the performance of ERPA is shown to remain constant regardless of the value taken by σ. This feature makes it an equally suitable choice for position location estimation in single hop or multihop scenarios. On the other hand, σ has a significant effect over the performance of RPA. As depicted in Fig. 3a RMSE decreases as σ increases for RPA, meaning that the accuracy of the position estimates provided by RPA will increase as the scenario approaches a single hop scheme.

As depicted in Fig. 3b, the number of available APs in the network is a parameter that has important effects on the estimation accuracy of DV-Hop, RPA, and ERPA. The scenario considered for this analysis consisted in a network with a fixed number of neighboring nodes ($N = 7.6$), therefore as the parameter σ was varied, the network node density had to be adjusted to keep the number of neighbors constant. Fig. 3b shows that, in this scenario, the estimation accuracy for RPA is considerably decreased as the number of APs is increased. This is due to the nature of the algorithm which relies on line λ_{ij} to sweep along the polygon segment connecting AP_i and AP_j. As the number

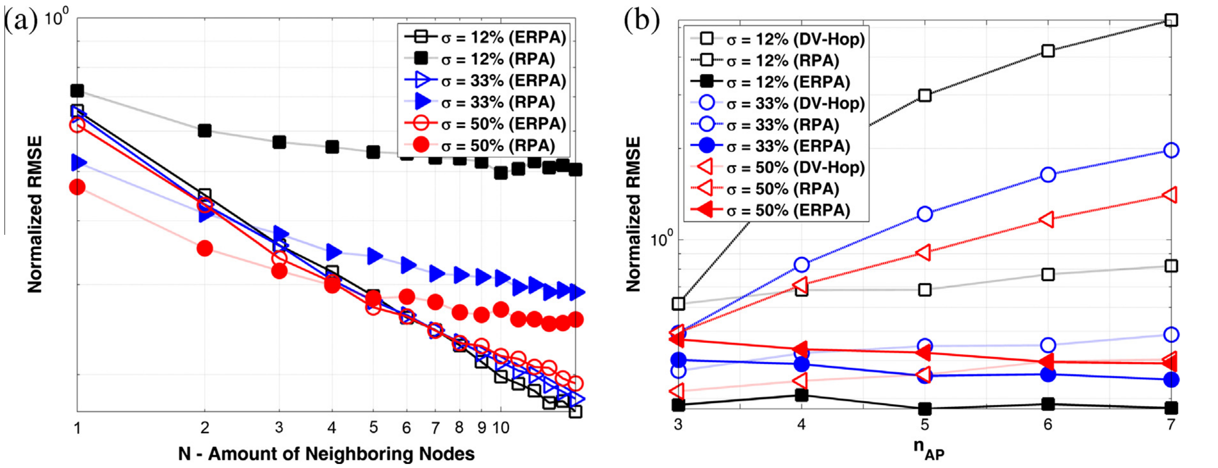

Fig. 3. Normalized RMSE (a) as a function of neighboring nodes and σ for RPA and ERPA and (b) as a function of the number of available APs in the network and σ for DV-Hop, RPA, and ERPA.

of APs is increased, λ_{ij} cannot longer sweep through the entire polygon area, creating zones where the accurate position estimation of the NOI becomes unfeasible. DV-Hop also shows a negative trend in which its estimation accuracy decreases as the number of available APs increases. Nonetheless, under this scenario it seems to be more robust than RPA, although it has the important drawback of requiring a preprocessing stage that significantly increases traffic overhead in the network. Finally, ERPA provides better accuracy as the number of available APs in the network is increased.

As it was observed that ERPA outperforms RPA for most scenarios, the rest of the simulation results are solely focused in ERPA. In Fig. 3 it was shown that with only a few neighboring nodes, and in the presence of noise-free distance measurements, ERPA is capable of providing high location estimation accuracy. Nonetheless, in a real scenario many sources of measurement noise exist (i.e., shadowing, scattering, multipath, etc.) Therefore, in order to analyze the effect of measurement errors in location estimation accuracy, additive measurement errors were assumed to occur with an exponential distribution with means ranging from of 5% to 20% of the actual distance measurements between NOI neighbors and the APs. In Fig. 4 we report normalized RMSE, both for noisy and noise-free scenarios. Comparison between Figs. 3a and 4a allow the identification of yet another advantage of ERPA over RPA, which is that with just a few neighboring nodes to work with, and even in the presence of measurement errors, ERPA exhibits better performance than RPA does in noise-free scenarios for small values of σ. Furthermore, Fig. 4b shows the effect of measurement errors as a function of σ and the amount of available APs in the network.

Fig. 4b allows the comparison of different distributions of APs to find what configuration best mitigates the effect of measurement errors. As it can be observed from the normalized RMSE curves, in the absence of measurement errors (Measurement Error Mean = 0 in the figure), the

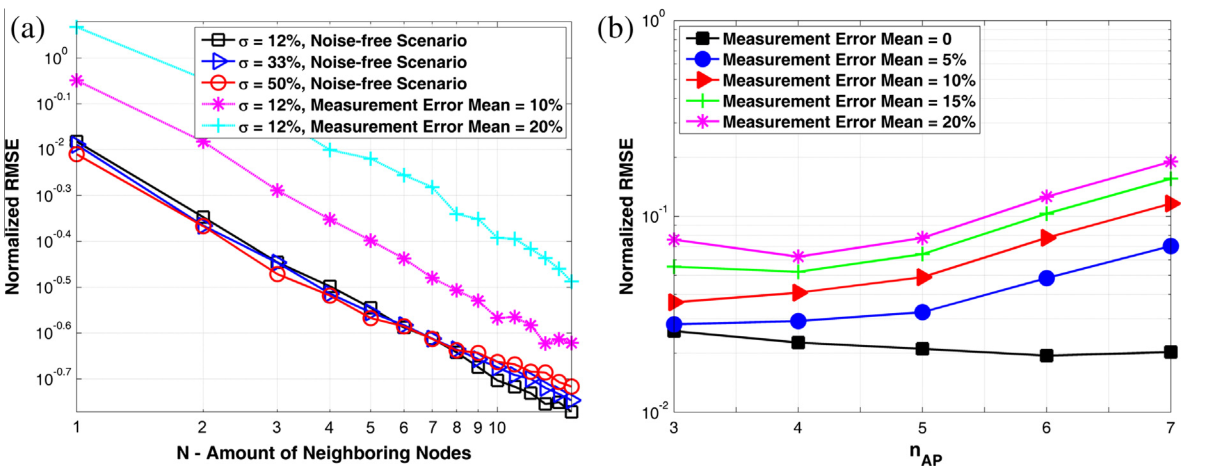

Fig. 4. Effect of measurement error over the normalized RMSE for ERPA as a function of (a) neighboring nodes and (b) available APs.

Table 1
Comparison between different position location algorithms.

Method	Network node density	Accuracy
RPA, σ = 50% (noise-free)	7.6 Neighbors per node and 3APs	26% R
ERPA (noise-free)	7.6 Neighbors per node and 3APs	22% R
ERPA (error mean = 10%)	7.6 Neighbors per node and 3APs	32% R
ERPA (error mean = 20%)	7.6 Neighbors per node and 3APs	47% R
APIT (noise-free)	16 One-hop APs	40% R
DV-Hop (noise-free)	7.6 Neighbors per node with 30% to be APs	30% R
DV-Distance (noise-free)	7.6 Neighbors per node with 30% to be APs	15% R
Euclidean (noise-free)	7.6 Neighbors per node with 30% to be APs	10% R
MDS-MAP (noise-free)	12.2 Neighbors per node and 3AP	50% R

estimation accuracy of the system is improved as the number of available APs is increased. Nonetheless, as the measurement error mean is increased the trend changes. Even with a measurement error mean of 5% the estimation accuracy of ERPA decreases as the number of APs increases. Nevertheless, as the measurement error mean is increased, the best configuration of APs changes from a triangle with three APs, to four-AP polygon.

In order to evaluate how accurate both proposed location estimation algorithms are, it is important to provide a benchmark for comparison. Table 1 shows such a comparison between the performances of the methods presented in this paper and those of previously published position location algorithms (data obtained from [3]). In order to fairly compare these algorithms we have considered scenarios with an average of 7.6 neighbors per node as in [3]. From Table 1 it can be observed that although RPA is outperformed by ERPA for most scenarios, RPA (accuracy of 26% R) can compete with techniques such as DV-Hop, APIT, and MDS-MAP for medium and large values of σ. On the other hand, ERPA exhibits a better performance than these three methods for any value of σ. Moreover, RPA and ERPA offer the advantage of requiring only three APs in the network, while DV-Hop, DV-Distance, Euclidean, and APIT approaches employ a large number of APs (e.g., APIT requires 16 one-hop APs). In addition, the proposed approaches do not require a preprocessing stage, as opposed to DV-Hop and DV-Distance, lowering the computational and communication costs.

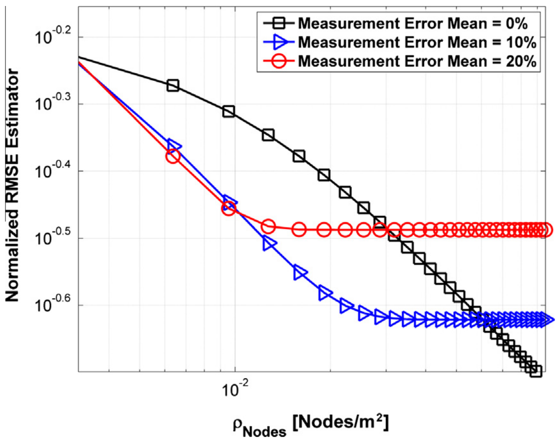

Fig. 5. Effect of measurement error over the normalized RMSE for ERPA as a function of area node density.

It is important to bear in mind that in a real scenario the number of neighbors is not a parameter to be controlled (but network node density is), because in a homogeneous scenario it is a Poisson distributed number. Fig. 5 shows the normalized RMSE in terms of the network node density (it is important to bear in mind that the estimation accuracy of ERPA is not dependent on σ and therefore any curve from Fig. 3 can be taken as the noise-free reference). It can be noted that the estimation accuracy of the algorithm improves as node density increases. However, as node density grows for noisy scenarios, the RMSE reaches a plateau determined by the distribution of the measurement error. At this point, the RMSE will no longer be dependent on node density.

6. Conclusions

In this work, we introduced two algorithms, RPA and ERPA, for position location in AHWSNs with neighbor cooperative information. Proposed heuristics determine the location of a Node of Interest (NOI) in terms of the number of nodes in the neighborhood surrounding the NOI. The proposed methodology can be applied to a wide variety of both indoor and outdoor scenarios, provided that proximity indicators are obtainable either via direct measurements or by the relations of the NOI to surrounding neighbors. The accuracy of the proposed location estimation methods relates to the available information as well as to the measurement errors caused by the range estimation techniques used and the propagation conditions. The algorithms proposed are based on the proximity indexes which can be defined depending on the distance estimation technique available in the network. Performance for several schemes has been examined and in order to have applicability to a wide range of scenarios, results are normalized with respect to the coverage radius of the NOI. Also, the impact of measurement noise, node density, and available APs is presented.

Results show that the location accuracy improves as the number of cooperating nodes increases, however, high node densities of neighboring nodes are not necessarily required to achieve a good localization accuracy. Furthermore, both RPA and ERPA methods were shown to present advantages over known location estimation techniques on the accuracy of the location estimation as a percentage of the coverage radius. Also, both RPA and ERPA were shown to provide advantages in terms of computational and communication costs. Furthermore, the proposed methods also reduce the number of APs needed to provide acceptable location estimation accuracy.

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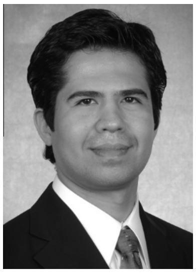

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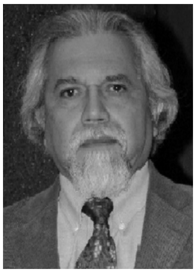

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