Robust ANNs-Based WSN Localization in the Presence of Anisotropic Signal Attenuation

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***Abstract*—We propose a novel range-free localization algorithm for wireless sensor networks that is robust against the anisotropic signal attenuation induced by fading, shadowing, interference, etc., present in any wireless channel, and hereby, develop a new distance estimation (DE) approach able to efficiently derive distances' estimates in closed form. Exploiting artificial neural networks, we also develop a power-efficient DE correction mechanism that properly accounts for anisotropic signal attenuation. Simulation results show that the proposed algorithm significantly outperforms most representative range-free localization algorithms, not only in accuracy but also in robustness against anisotropic attenuation.**

***Index Terms*—Localization, wireless sensor networks (WSNs), artificial neural networks (ANNs), radio propagation pattern (RPP), anisotropic signal attenuation, cost and power efficiencies, robustness.**

I. Introduction

LOCALIZATION is crucial for many WSN applications such as environment monitoring, disaster relief, and target tracking [1]. So far, several localization algorithms have been proposed in the literature. These algorithms can be roughly classified into two categories: range-based and range-free [2]–[4]. To properly localize the regular or position-unaware node positions, range-based algorithms exploit the measurements of some specific received signals' characteristics such as the time of arrival (TOA), the angle of arrival (AOA), or the received signal strength (RSS). These signals are, in fact, transmitted by nodes aware of their positions called anchors (or landmarks). Although range-based algorithms are very accurate, in general, they are unsuitable for WSNs. Indeed, these algorithms require high power to ensure communication between anchors and regular nodes which are small battery-powered units. Furthermore, additional hardware is usually required at both anchors and regular nodes, thereby increasing the overall cost of the network. Unlike range-based algorithms, range-free algorithms, which rely on the network connectivity to estimate the regular node positions, are more power-efficient and do not require any additional hardware and, hence, are suitable for WSNs. Due to their practical merits, range-free localization algorithms have garnered the attention of the research community. The range-free techniques developed so far fall in two classes: heuristic and analytical [5]–[7]. Heuristic algorithms are more or less a variation of the well-known DV-HOP [5] whose implementation in WSNs requires the overhead-burdened calculation (by input reception) and broadcast (by output transmission) of a correction factor by each anchor. Such undesired impediment incurs prohibitive overhead and power consumption thereby increasing the overall cost of the network. On the other hand, analytical algorithms evaluate theoretically the distances between the anchors and regular nodes [6], [7]. These distances are in fact locally computable at each node, thereby avoiding the above-mentioned impediments of heuristic algorithms. In spite of their valuable contributions, these techniques rely on the unrealistic assumption that nodes have a circular radio propagation pattern (RPP) [6], [7]. However, due to real-world phenomena such as fading, shadowing, and interference, etc., present in any wireless channel, anisotropic signal attenuation (i.e., different from a direction to another) occurs, thereby resulting in practice to irregular nodes' RPPs [8]. Hence, if the latter are not properly taken into account, distance estimation (DE) errors increase significantly and severely hinder localization accuracy.

In this letter, we propose a novel analytical algorithm robust against the anisotropic signal attenuation and develop a new DE approach able to efficiently derive distances' estimates in closed form. Exploiting ANNs, we also develop a power-efficient DE correction mechanism that properly accounts for anisotropic signal attenuation. Simulation results show that the proposed algorithm outperforms most representative range-free localization algorithms, not only in accuracy, but also in robustness against anisotropic attenuation.

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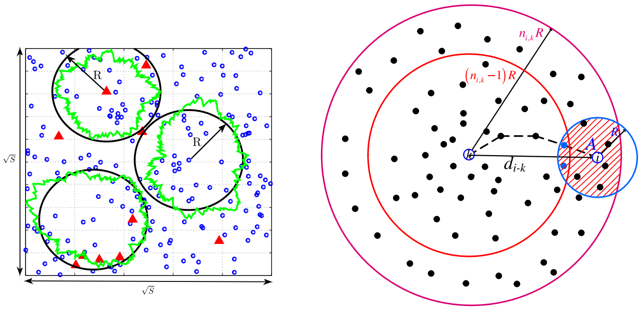
II. Network Model

Fig. 1(a) illustrates the system model of N WSN nodes uniformly and independently deployed in a 2-D square area S. Due to the high cost of the global positioning system (GPS) technology, only a few nodes commonly known as anchors are equipped with it and, hence, are aware of their positions. The other nodes, called hereafter position-unaware or regular nodes for the sake of simplicity, are oblivious to this information. In Fig. 1(a), the anchor nodes are marked with red triangles while the regular ones are marked with blue discs. Without loss of generality, let (x_i, y_i), $i = 1, \ldots, N_a$ be the coordinates of the anchor nodes and (x_i, y_i), $i = N_a + 1, \ldots, N$ those of the regular ones. All nodes are assumed to have the same transmission capability (i.e., range) denoted by R. An anisotropic signal attenuation (i.e., varies from a direction to another) is also assumed, due to phenomena such as fading, shadowing, and interference, etc., present in any wireless channel. This leads, as illustrated in Fig. 1(a), to irregular RPPs. Hence, the green curves there represent the nodes' irregular RPPs while the black circles represent their idealistic ones (i.e., without accounting for fading, shadowing, and interference, etc.).



(a) Network model. (b) Distance estimation.

Fig. 1. System model and distance estimation mechanism.

In what follows, we propose an efficient localization algorithm which accounts for the nodes' irregular RPPs when estimating the regular nodes' positions. Such an algorithm requires that these nodes estimate their distances to 3 anchors, at least, and be aware of their coordinates [5]–[7]. The more accurate is DE, the more reliable is localization. Hence, we propose in the next section a novel DE approach for proper integration later in our proposed WSN localization algorithm.

III. Proposed DE Approach

So far, in most previous algorithms, the i-th regular node (i.e., (N_a+i)-th node) estimates its distance to the k-th anchor d_{i-k} as

$$\hat{d}_{i-k} = n_{i,k} h_{\mathrm{av}}, \tag{1}$$

where $n_{i,k}$ is the number of hops between the two nodes and h_{av} is a predefined average hop size (AHS). Unfortunately, this approach exhibits a major drawback. Indeed, AHS is usually derived either analytically by exploiting the Poisson Limit Theorem valid for high nodes densities [6], [7] or heuristically by computing the mean hop size of all the shortest paths between anchors [5]. It is, however, very likely that AHS be different from the mean hop size of the shortest path between the k-th and (N_a+i)-th nodes (i.e., $h_{\mathrm{av}} \neq (\sum_{l=1}^{n_{i,k}} h_l)/n_{i,k}$ where h_l is the l-th hop's size). Hence, large DE errors may occur, thereby hindering the i-th regular node's localization accuracy. In order to circumvent this issue, we propose in this letter to directly estimate d_{i-k} without resorting to the AHS. Indeed, it was shown that the minimum mean square error (MMSE) of the distance estimation can be obtained if [7]

$$\hat{d}_{i-k} = \mathrm{E}\{Z|n_{i,k}\}, \tag{2}$$

where Z denotes the random variable that represents the real distance d_{i-k}, and $\mathrm{E}\{\cdot|n_{i,k}\}$ is the expectation conditioned on $n_{i,k}$. However, due to the randomness of the nodes' irregular RPPs, the derivation of $\hat{d}_{i-k}$ in closed form is a priori a very tedious task, if not impossible. For the sake of both simplicity and tractability, we assume herein, only temporarily, idealistic circular RPPs (i.e., there is no interference, fading or shadowing) when computing $\hat{d}_{i-k}$. In the next section, we will propose a correction mechanism that properly accounts for the effects of the nodes' irregular RPPs in the calculation of $\hat{d}_{i-k}$.

Assuming idealistic circular nodes' RPPs, it is straightforward to show that the i-th regular node is located, as illustrated in Fig. 1(b), in the area

$$A = D\big(k, n_{i,k}R\big) \cap D(i, R), \tag{3}$$

where $D(\star, x)$ is the disc having the $\star$-th node as a center and x as a radius. An in-depth look at this figure reveals that d_{i-k} is strongly dependent on A. Indeed, the smaller is d_{i-k} the wider is the area A, and vice-versa the larger is the former the narrower is the latter. $\hat{d}_{i-k}$ could be then obtained by averaging d_{i-k} over all possible values of A and, hence, we have

$$\hat{d}_{i-k} = \int_{A_{\mathrm{Min}}}^{A_{\mathrm{Max}}} \Psi(A)\, f_A(a)\, da, \tag{4}$$

where $\Psi(A)$ is the functional relationship between d_{i-k} and A, A_{Max} and A_{Min} are the maximum and minimum value of the latter, respectively, and $f_A(a)$ is its probability density function (pdf). According to (4), it is clear that $\Psi(A)$ and $f_A(a)$ are crucial to obtain $\hat{d}_{i-k}$'s expression. First, let us focus on $\Psi(A)$. Using some geometrical properties and trigonometric transformations, one can show that [9]

$$\begin{aligned} A = \Phi(d_{i-k}) &= R^2 \cos^{-1}\left(\frac{d_{i-k}^2 + R^2\big(1 - n_{i,k}^2\big)}{2Rd_{i-k}}\right) \\ &\quad + n_{i,k}^2 R^2 \cos^{-1}\left(\frac{d_{i-k}^2 - R^2\Big(1 - n_{i,k}^2\Big)}{2n_{i,k}Rd_{i-k}}\right) \\ &\quad - \frac{1}{2}\sqrt{\big(R^2(1+n_{i,k})^2 - d_{i-k}^2\big)\big(d_{i-k}^2 - R^2(1-n_{i,k})^2\big)}, \end{aligned} \tag{5}$$

where $\Phi = \Psi^{-1}$ is the inverse function of Ψ. As $\Phi(d_{i-k})$ is a complex function of d_{i-k}, $\Psi(A)$ cannot be unfortunately obtained in closed form. We will, however, prove in the sequel that it is possible to compute the integral in (4) by solely exploiting the right-hand-side (RHS) of (5). Now let us turn our attention to $f_A(a)$. From (5), the computation of the latter in closed form turns out to be impossible, to the best of our knowledge. For the sake of mathematical tractability, in what follows, A is assumed to be uniformly distributed in $[A_{\mathrm{Min}}, A_{\mathrm{Max}}]$. Despite this simplifying assumption, we will shortly see in Section V that the proposed algorithm provides much better accuracy than the most representative range-free algorithms currently available in the literature. Using (5) alongside the fact that A_{Max} occurs when $d = (n_{i,k}-1)R$ and A_{Min} occurs when $d = (n_{i,k})R$, we have

$$\begin{aligned} f_A(a) = \frac{1}{\Delta A} = \frac{1}{A_{max} - A_{min}} &= \left(R^2\left(\pi - \cos^{-1}\left(\frac{1}{2n_{i,k}}\right)\right.\right. \\ &\quad \left.\left. - n_{i,k}^2 \cos^{-1}\left(1 - \frac{1}{2n_{i,k}^2}\right) + \frac{1}{2}\sqrt{4n_{i,k}^2 - 1}\right)\right)^{-1}. \end{aligned} \tag{6}$$

In order to compute $\hat{d}_{i-k}$, we propose to resort to the variable change $z = d_{i-k} = \Psi(A)$ in the integral of (4). This implies that $dz = \Psi^{(1)}(A)\, da$ where $\Psi^{(1)}$ is the first derivative of Ψ given by

$$\begin{aligned} \Psi^{(1)}(A) &= \Big(\Phi^{(1)}\Big(\Psi^{(1)}(A)\Big)\Big)^{-1} = \Big(\Phi^{(1)}(z)\Big)^{-1} \\ &= -z\Big/\sqrt{2\Big(1+n_{i,k}^2\Big)R^2z^2 - \Big(n_{i,k}^2 - 1\Big)^2 R^4 - z^4}, \end{aligned} \tag{7}$$

where $\Phi^{(1)}$ is the first derivative of Φ. Actually, this key property - that the inverse function's first derivative depends only on the original function's first derivative - is the one to allow us compute $\hat{d}_{k-i}$ as

$$\hat{d}_{i-k} = \frac{1}{\Delta A}\int_{(n_{i,k}-1)R}^{n_{i,k}R} \sqrt{2\Big(1+n_{i,k}^2\Big)R^2z^2 - \Big(n_{i,k}^2-1\Big)^2 R^4 - z^4}\, dz. \tag{8}$$

In (8), please note that we account for the fact that if $A = A_{\mathrm{Max}}$ (or, $A = A_{\mathrm{Min}}$), then $z = (n_{i,k}-1)R$ (or, $z = n_{i,k}R$). It is also noteworthy that the integral in (8) can be easily obtained in closed form expressed using Elliptic functions. It follows from (8) that $\hat{d}_{i-k}$ depends solely on R and $n_{i,k}$ which will be shown to be locally available at every regular node in the next sections.

IV. Proposed Localization Algorithm

We propose in this section a novel three-step localization algorithm. In the first step, the regular nodes receive in a multi-hop fashion all the information required to estimate their respective distances to all anchors using the DE approach developed in (8). In the second step, a correction mechanism that properly accounts for the effects of the real irregular nodes RPPs is locally performed at each node in order to minimize the DE errors. In the third and last step, the regular nodes' positions are computed using the obtained distances alongside the anchors positions by resorting to conventional multilateration. Due to space limitation, only steps one and two are described in the following. Interested readers can be, however, referred to [2] for ample details on the multilateration process.

A. Step 1: Initialization

As a first step of any anchor-based localization algorithm, the k-th anchor broadcasts through the network a packet which consists of a header followed by a data payload. The header contains the anchor position (x_k, y_k) while the data payload contains the hop-count value n initialized to one. When a node receives this packet, it stores the k-th anchor position as well as the received hop-count $n_k = n$ in its database, increments the latter (i.e., $n = n + 1$), and then broadcasts the resulting message. Once this message is received by an another node, its database information is checked. If the k-th anchor information is already available and the received hop-count value n is smaller than the one previously stored n_k, the node updates the latter, increments n by 1, then broadcasts the resulting message. If n_k is smaller than n, the node discards the received message. However, when the node is oblivious to the k-th anchor position, it adds this information to its database and forwards the received message after incrementing n by 1. This mechanism will continue until all nodes become aware of all anchors' positions and their corresponding minimum hops' numbers. Using its available information, the i-th regular node is then able to compute an estimate $\hat{d}_{i-k}$ of its distance to the k-th anchor using the DE approach developed in (8). Unfortunately, since this approach does not account for the real irregular nodes' RPPs significant errors occur, thereby hindering severely localization accuracy. In the sequel, we propose a new DE correction mechanism that properly accounts for the effects of the real irregular nodes' RPPs.

B. Step 2: Distance Correction

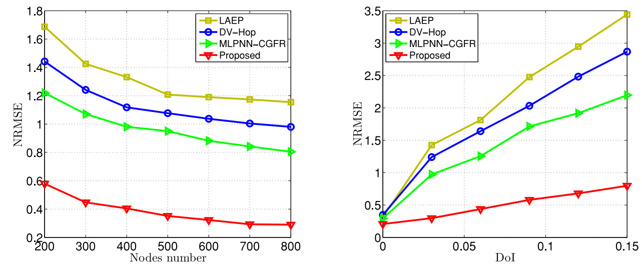
An important feature that might allow substantial reduction of DE errors, if properly exploited, is that anchors are fully aware of their true inter-distances and, further, could easily estimate them from (8). In order to capitalize on these data (i.e., true and estimated anchor inter-distances), we propose the exploitation in this letter of ANNs due to their ability to build the complex relationship between the true and estimated distances. ANNs consist of groups of interconnected artificial neurons. Depending on the nature of these neurons' connections, several types of ANNs exist in [10]–[12]. In this letter, we only consider the multi-layer perceptron (MLP)-type feed-forward back-propagation ANNs whose efficiency has been already proven in the context of WSN localization [10]. Using all the estimated distances between anchors as inputs and the true distances as outputs of the ANN during the learning phase, we are able to generate a model or a set of parameters also known as weights and biases that governs the ANN's input-output relationship or function. It is the use of the latter through the very same ANN type at the regular nodes during the so-called generalization phase, i.e., over previously unobserved data, that allows extrapolation - through the very same linkage established over anchor inter-distances - any new ANN-input distances $\hat{d}_{i-k}$ estimated at the regular nodes assuming idealistic circular RPPs into ANN-output calibrated ones $\bar{d}_{i-k}$ that properly account for real irregular RPPs.

Nevertheless, one pending issue needs to be addressed before of our new ANN-based distance correction mechanism can be implemented properly. Indeed, as discussed above, the latter imperatively requires a training phase that must necessarily be performed at a node with large power resources. In this letter, we propose that one of the anchors, called hereafter super anchor, play this role (i.e., generation through training then broadcast for generalization at other nodes the obtained generic ANN model throughout the network). The main reason for this choice is that an anchor already stores a good part of the required training data and, hence, allows substantial overall reduction of overhead, hardware complexity, and power. Actually, in many applications some anchors are nothing but access points (AP)s with large-enough power resources. Should such APs be unavailable, the so-called super anchor could be equipped with a longer lifetime battery (and/or even energy-harvesting capabilities) that maintains an adequate power level for all its tasks to be achieved.

Furthermore, to be able to perform ANN training, the super anchor needs to be aware of all true and estimated anchor inter-distances (i.e., $N_a(N_a - 1)$ distance pairs). Each anchor should be then solicited for a second power and overhead consuming broadcast to share its data with the super anchor. To avoid this situation, we propose in what follows a power-efficient information sharing protocol where anchors periodically broadcast their positions alongside the training data. In fact, during the first time slot, only the super anchor should broadcast its position while the $(N_a - 1)$ other anchors only execute the tasks described in Section IV-A. At the second time slot, one of the latter calculates its pair true (e.g., GPS-based) and estimated (as described in Section III) distances to the super anchor then broadcast it along with its own position throughout the network. Upon reception of these information, all nodes become a priori aware of the super anchor and first anchor positions and their inter-distance pairs. A second anchor then calculates its true and estimated inter-distances to both the super and first anchors and broadcasts them along with its position throughout the network. Within N_a time slots, all nodes, including the super anchor, become a priori aware of all the anchors' positions and all $N_a(N_a - 1)/2$ inter-distance pairs (i.e., true and estimated). Please note here that each anchor broadcasts information only one time, thereby allowing huge overhead and power savings with respect to the protocol adopted in [10]. This benefit comes, however, at the cost of a reduced training data size. Indeed, with our protocol, the super anchor is able to progressively accumulate up to $(N_a^2 + N_a - 2)/2$ distance pairs while a relatively larger training data could be collected if each anchor were to broadcast separately its position and distances as done in [10]. Nevertheless, we will show below that the one gathered through the proposed power-efficient information sharing protocol is more than enough for the proposed ANN-based WSN localization technique to outperform most representative range-free algorithms currently available in the literature.

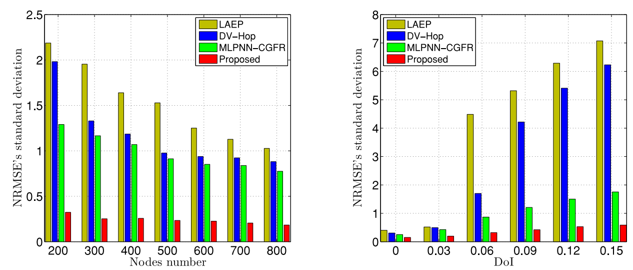
V. Simulations Results

Monte-Carlo simulations are provided in this section to support the theoretical and analytical results established previously. These simulations are conducted to compare, under the same network settings, the proposed algorithm with three of the best benchmarks currently available in the literature, namely, DV-Hop [5], LAEP [6], and MLPNN-CGFR [10]. All simulation results are obtained by averaging over 500 trials. In all simulations, nodes are uniformly deployed in a 2-D square



(a) DoI = 0.06. (b) $N = 300$.

Fig. 2. Localization NRMSE achieved by the proposed algorithm and its counterparts for different values of N and DoI.



(a) DoI = 0.06. (b) $N = 300$.

Fig. 3. NRMSE's standard deviation achieved by the proposed algorithm and its counterparts for different values of N and DoI.

area $S = 10^4 m^2$ and R and N_a are, respectively, set to $18m$ and 20. Furthermore, a nodes' RPP model characterized by a degree of irregularity (DoI) similar to that in [8] is considered. As a performance metric, we propose the normalized root mean square error (NRMSE) defined as

$$\text{NRMSE} = \left(\sum_{i=1}^{N-N_a} \sqrt{\left(x_i - \hat{x}_i\right)^2 + \left(y_i - \hat{y}_i\right)^2} \right) / ((N - N_a)R). \tag{9}$$

Fig. 2 plots the localization NRMSE achieved by the proposed algorithm, LAEP, DV-Hop, and MLPNN-CGFR for different values of N and DoI. As can be observed there, the proposed algorithm always outperforms its counterparts as it turns out to be until about four, three, and two times more accurate than LAEP, DV-Hop, and MLPNN-CGFR, respectively. In Fig. 2(b), the localization NRMSE achieved by all algorithms deteriorates as expected with DoI. However, the proposed algorithm show much more robustness to DoI and its accuracy losses than its counterparts.

Fig. 3(a) and 3(b) plot the NRMSE's standard deviation achieved by all localization algorithms for different values of N and DoI, respectively. They show that it decreases as expected for all algorithms when the node density increases. However, the one achieved by our algorithm, in contrast to its counterparts, remains relatively very small and even approaches zeros when N becomes large enough. Furthermore, Fig. 3(b) shows that the NRMSE's standard deviation's increase with the DoI is relatively slow and moderate with the proposed algorithm, but steep and significant with all three benchmarks.

Fig. 4 illustrates the NRMSE's CDF achieved by all algorithms and suggests that 99% of the sensors could estimate their position within a NRMSE value of less than 1 with the proposed technique. In contrast, only 61% of the nodes achieve the same accuracy with MLPNN-CGFR, 43% with Dv-Hop, and only 30% with LAEP. This further proves the superiority of our new WSN localization algorithm over its counterparts in the presence of anisotropic signal attenuation.

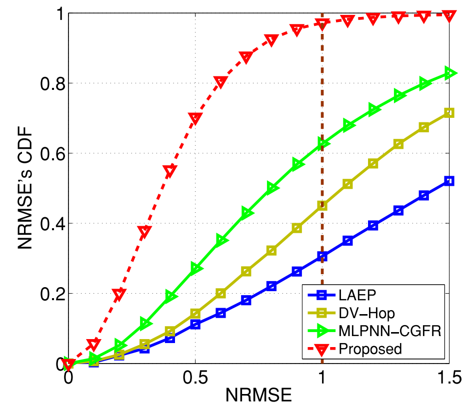


Fig. 4. NRMSE's CDF achieved by the proposed algorithm and its counterparts for $N = 300$ and DoI = 0.06.

VI. Conclusion

In this letter, we proposed a novel range-free localization algorithm robust against the anisotropic signal attenuation induced by fading, shadowing, and interference, etc., present in any wireless channel. To do so, we developed a new DE approach able to efficiently derive distance estimates in closed form. We also developed an ANN-based power-efficient DE correction mechanism that accounts for anisotropic signal attenuation. The proposed algorithm significantly and unambiguously outperforms most representative range-free localization algorithms, not only in accuracy, but also in robustness against anisotropic attenuation.

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