Range-Free Localization Algorithm for Heterogeneous Wireless Sensor Networks

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***Abstract*—In this paper, we propose a novel range-free localization algorithm tailored for heterogeneous wireless sensor networks (WSNs), where nodes have different transmission capabilities. Two different approaches are developed to accurately derive the expected hop progress (EHP). It is shown that the obtained EHP depends solely on the information locally available at each node and, hence, can be computed in a localized manner. Furthermore, a localization correction mechanism which accounts for the heterogeneous nature of WSNs is developed. Simulations results show that the proposed algorithm, whether with or without correction, outperforms in accuracy the most representative range-free localization algorithms in the literature.**

***Index Terms*—Heterogeneous wireless sensor networks, localization accuracy, range-free, expected hop progress, distance estimation.**

I. Introduction

Due to their reliability, low cost, and ease of deployment, wireless sensor networks (WSNs) are emerging as a key tool for many applications such as environment monitoring, disaster relief, and target tracking [1]-[2]. A WSN is a set of small battery-powered sensors able to collect data from the surrounding environment and transmit it to a base station or an access point [3]. However, the sensing data are very often useless if the location from where they have been measured is unknown, making their localization a fundamental and essential issue in WSNs. 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.

To properly localize the regular or position-unaware nodes, range-based algorithms exploit the measurements of the received signals' characteristics such as the time of arrival (TOA) [4], the angle of arrival (AOA) [5], or the received signal strength (RSS) [6]. These signals are, in fact, transmitted by nodes with prior knowledge of their positions called anchors (or landmarks). Although range-based algorithms are very accurate, 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 [7], thereby increasing the overall cost of the network. Moreover, the performance of these algorithms can be severely affected by noise, interference, and/or fading.

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 these practical merits, range-free localization algorithms have garnered the attention of the research community. So far, many range-free algorithms have been proposed in the literature [8]- [19]. These algorithms mainly fall into two categories: heuristic and analytical. The majority of heuristic algorithms are based on the DV-Hop algorithm [11]. The latter allows derivation of the network's average hop size, also known as expected hop progress (EHP), from the global information of the WSN in a nonlocalized manner, thereby resulting in a prohibitive overhead and, hence, unnecessary high power consumption. Analytical range-free algorithms are, in contrast, more power efficient [13]-[18]. Indeed, these algorithms are based on an accurate analytical evaluation of the EHP which can be locally computed at each node, thereby avoiding unnecessary power consumption. In spite of their valuable contributions, the approaches developed in [13]-[18] to derive the EHP are based on the unrealistic assumption that all sensors have the same transmission capabilities (i.e., the WSN is homogenous). To the best of our knowledge, there is no analytical range-free algorithm which accounts for the heterogeneous nature of WSNs.

To fill this gap, we propose in this paper a novel analytical range-free algorithm tailored for heterogeneous WSNs where nodes have different transmission capabilities. Two different approaches are developed to accurately derive the EHP. It is shown that the obtained EHP depends solely on the information locally available at each node and, hence, can be computed in a localized manner. Furthermore, a localization correction mechanism which accounts for the heterogeneous nature of WSNs is developed in this work. Simulations results show that the proposed algorithm, whether with or without correction, outperforms the most representative heuristic and analytical range-free localization algorithms in terms of accuracy.

The rest of this paper is organized as follows: Section II describes the system model. Section III discusses the motivation for this work. Section IV derives the EHP using two approaches. A novel range-free localization algorithm is proposed in section V. Simulation results are discussed in Section VI and concluding remarks are made in section VII.

Notation: Uppercase and lowercase bold letters denote matrices and vectors, respectively. $[\cdot]_{il}$ and $[\cdot]_i$ are the (i,l)-th entry of a matrix and i-th entry of a vector, respectively. $\mathbf{I}$ is the identity matrix. $(\cdot)^T$ denotes the transpose. $D(i,x)$ denotes the disc having the i-th node as a center and x as a

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radius.

II. Network model

Fig. 1 illustrates the system model of N WSN nodes deployed in a 2-D square area S. Due to the heterogeneous nature of WSNs, nodes are assumed here to have different transmission capabilities. The transmission coverage of each node is assumed to be circular, i.e., the i-th node could directly communicate with any node located in $D\left(i, Tc_i\right)$, the disc having this node as a center and its transmission capability Tc_i as a radius. In a multi-hop transmission, note that the i-th node could also communicate with any node located outside its coverage area $D\left(i, Tc_i\right)$. It is also assumed that only a few nodes commonly known as anchors 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. As shown in Fig. 1, the anchor nodes are marked with red squares and the regular ones are marked with blue crosses. If a node is located within the coverage area of an another node, the two nodes are linked with a dashed line that represents one hop. Three discs were drawn as few illustrative examples of the coverage areas of the corresponding nodes. Let N_a and $N_u = N - N_a$ denote the number of anchors and regular nodes, respectively. Without loss of generality, let $\left(x_i, y_i\right)$, $i = 1, \ldots, N_a$ be the coordinates of the anchor nodes and $\left(x_i, y_i\right)$, $i = N_a + 1, \ldots, N$ those of the regular ones. In the following, we propose an efficient range-free localization algorithm aiming to accurately estimate the regular nodes' positions.

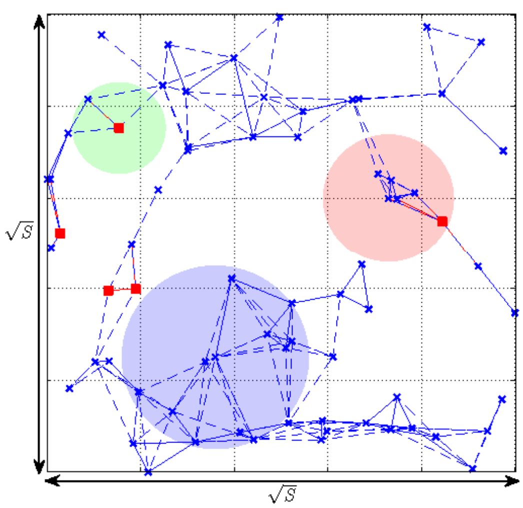

Fig. 1. Network model.

III. Range-free localization in heterogeneous WSN

As a first step of any range-free localization algorithm, the k-th anchor broadcasts through the network a message containing its position. If the $(i - N_a)$-th regular node (or the i-th node) is located outside the anchor coverage area, it receives this message through multi-hop transmission. For simplicity, let us assume that only one intermediate node j located over the shortest path between the k-th anchor and the i-th node is necessary (i.e., two-hop transmission). Assuming a high nodes density in the network, the distance d_{k-i} between the two nodes can be accurately approximated as [8]-[19]

$$d_{k-i} \approx d_{k-j} + d_{j-i}, \tag{1}$$

where $d_{\star-*}$ is the effective distance between the $\star$-th and the $*$-th node. The fundamental problem in every range-free localization algorithm is then to estimate d_{k-i} exploiting the aforementioned approximation. Borrowed from the literature [13]-[18], the most and commonly used estimation of d_{k-i} in the context of range-free localization is

$$\hat{d}_{k-i} = \mathrm{E}\left\{d_{k-i}\right\} \approx \bar{d}_{k-j} + \bar{d}_{j-i}, \tag{2}$$

where $\bar{d}_{k-j} = \mathrm{E}\left\{d_{k-i}\right\}$ is the expected hop progress (EHP) and $\bar{d}_{j-i} = \mathrm{E}\left\{d_{j-i}\right\}$ is the mean last hop (MLH).

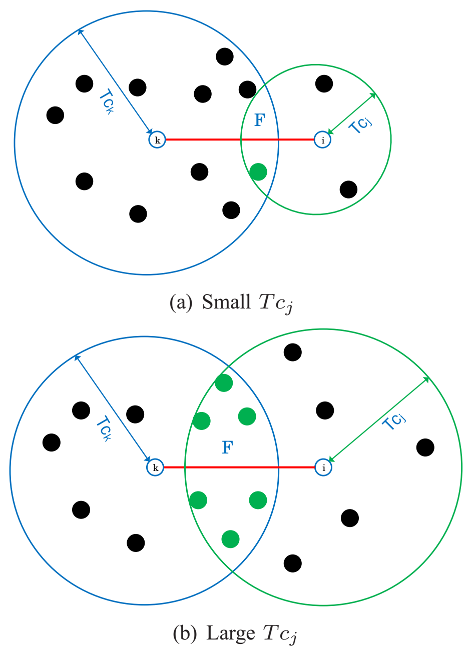

Fig. 2. Effect of intermediate node transmission capability.

Several approaches have been so far developed to compute the EHP $\bar{d}_{k-j}$ such as in [13]-[18]. It was shown in all these works that the EHP depends only on the anchor transmission capability Tc_k. In what follows, we will prove that this result is incorrect. Let us first denote by F the potential forwarding area wherein the intermediate node j could be located. Since this node should, at the same time, be located in the k-th node coverage area and communicate directly with the i-th node using its transmission capability Tc_j, F is given by

$$F = D(k, Tc_k) \cap D(i, Tc_j). \tag{3}$$

It is noteworthy that the EHP is nothing but the mean of all distances between the k-th node and all the potential intermediate nodes located in F and, hence, the EHP strongly depends on F. As can be observed from Fig. 2, if the intermediate node transmission capability Tc_j increases, the potential forwarding area F increases to include potential intermediate nodes closer to the k-th anchor, thereby increasing the EHP. Consequently, the EHP depends not only on Tc_k, but also on Tc_j. Let us now turn our attention to the MLH. It is obvious that the transmission capability of the i-th node does not have any effects on the last hop size d_{j-i}. Therefore, in contrast with the EHP, the MLH depends only on the transmission capability of the transmitting node j. In the next section, novel approaches are developed to accurately derive the expressions of both the MLH and the EHP.

IV. Analytic Evaluation of the MLH and the EHP

In this section, the expression of the MLH as well as the EHP are accurately derived. To this end, we consider the same scenario described in Section II. For the sake of clarity, in what follows, we denote by X, Y, and Z the random variables that represent d_{k-i}, d_{j-i}, and d_{k-j}, respectively.

A. MLH derivation

Since the i-th regular node could be located anywhere in $D(j, Tc_j)$ (the j-th node coverage area) with the same probability, Y can be considered as a uniformly distributed random variable on $[0, Tc_j]$. Therefore, the MLH denoted hereafter by $h^{\text{last}}(Tc_j)$ is given by

$$h^{\text{last}}(Tc_j) = \int_0^{Tc_j} y f_Y(y) dy = \int_0^{Tc_j} \frac{y}{Tc_j} dy = \frac{Tc_j}{2}, \quad (4)$$

where $f_Y(y) = 1/Tc_j$ is the probability density function (pdf) of Y.

B. EHP derivation

In order to derive the EHP, one should first compute the conditional cumulative distribution function (CDF) $F_{Z|X}(z) = P(Z \leq z|x)$ of Z with respect to the random variable X. In the following, two approaches are proposed to derive this CDF.

1) Approach 1: As can be shown from Fig. 3, $Z \leq z$ is guaranteed only if there are no nodes in the dashed area A. Therefore, the conditional CDF $F_{Z|X}(z)$ can be defined as

$$F_{Z|X}(z)(z) = P(Z \leq z|x) = P(\mathrm{E}_1), \quad (5)$$

where $P(\mathrm{E}_1)$ is the probability that the event $\mathrm{E}_1 = \{$no nodes in the dashed area $A\}$ occurs. Since the nodes are uniformly deployed in S, the probability of having K nodes in A follows a Binomial distribution $\mathrm{Bin}(N, p)$ where $p = \frac{A}{S}$. For relatively large N and small p, it can be readily shown that $\mathrm{Bin}(N, p)$ can be accurately approximated by a Poisson distribution $\mathrm{Pois}(\lambda A)$ where $\lambda = N/S$ is the average nodes density in the network. Consequently, for a large number of nodes N and small p, we have

$$F_{Z|X}(z) = e^{-\lambda A}. \quad (6)$$

Using some geometrical properties and trigonometric transformations, it is straightforward to show that

$$A = Tc_k^2\left(\theta - \frac{\sin(2\theta)}{2}\right) + Tc_j^2\left(\theta' - \frac{\sin(2\theta')}{2}\right) - z^2\left(\theta_z - \frac{\sin(2\theta_z)}{2}\right) + Tc_j^2\left(\theta_z' - \frac{\sin(2\theta_z')}{2}\right), \quad (7)$$

where $\theta = \arccos\left(\frac{Tc_k^2 - Tc_j^2 + x^2}{2Tc_k x}\right)$, $\theta' = \arccos\left(\frac{Tc_j^2 - Tc_k^2 + x^2}{2Tc_j x}\right)$, $\theta_z = \arccos\left(\frac{z^2 - Tc_j^2 + x^2}{2zx}\right)$, and $\theta_z' = \arccos\left(\frac{Tc_j^2 - z^2 + x^2}{2Tc_j x}\right)$.

Finally, the EHP $h(Tc_k, Tc_j)$ between the k-th and j-th nodes can be derived as

$$h(Tc_k, Tc_j) = \mathrm{E}_x\left(\alpha\left(1 - F_{Z|X}(\alpha)\right) + \int_\alpha^{Tc_k}\left(1 - F_{Z|X}(z)\right)dz\right)$$
$$= \int_{Tc_k}^{Tc_k+Tc_j}\left(\alpha\left(1 - F_{Z|X}(\alpha)\right) + \int_\alpha^{Tc_k}\left(1 - F_{Z|X}(z)\right)dz\right) f_X(x)dx, \quad (8)$$

where $\alpha = x - Tc_j$ and $f_X(x)$ is the pdf of X. Note that the latter can be considered as a uniform random variable over $[Tc_k, Tc_k + Tc_j]$ and, hence, $f_X(x)$ can be substituted in the latter result by $1/Tc_j$. To the best of our knowledge, a closed-form expression for the EHP in (8) does not exist. However, $h(Tc_k, Tc_j)$ can be easily implemented since it depends on finite integrals.

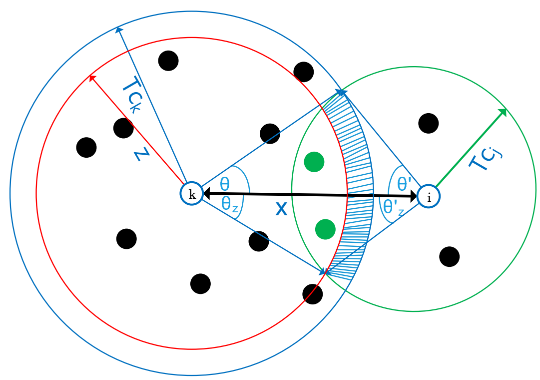

Fig. 3. EHP analysis.

2) Approach 2: The main issue with the approach developed above is that it only holds when the number of nodes N is sufficiently large and the area A is much smaller than the network size. Since N is typically large in the context of WSNs, the first condition is very likely to be satisfied. Unfortunately, the second condition cannot be always guaranteed, especially when the transmission capabilities Tc_k and Tc_j are relatively large. Indeed, in such a case A is very likely to be large and, hence, the EHP derived using the above CDF is no longer accurate. In this section, we propose another approach aiming to derive this CDF for any N, Tc_k and Tc_j.

Let us assume that M potential intermediate nodes exist between the i-th and k-th node, or, in other words, M potential positions of the intermediate node j exist in F. Let Z_m be the random variable that represents the distance between the k-th node and the m-th potential intermediate node. Thus, one can define $F_{Z|X}(z)$ as follows

$$F_{Z|X}(z) \quad = \quad P\left(Z_1 \le z \cap Z_2 \le z, \ldots, \cap Z_M \le z\right). \quad (9)$$

Using the fact that $Z_m, m = 1, \ldots, M$ are independently and identically distributed (i.i.d) random variables, we obtain

$$F_{Z|X}(z) \quad = \quad P\left(Z_m \le z\right)^M. \quad (10)$$

As can be observed from Fig. 3, in order to satisfy $Z_1 \le z$, the m-th intermediate node should be located in the area $B = F - A$ and, hence,

$$F_{Z_1|X}\left(z\right) = P\left(Z_1 \le z|x\right) = P\left(\mathrm{E}_2\right), \quad (11)$$

where $P(\mathrm{E}_2)$ is the probability that the event $\mathrm{E}_2 = \{$the m-th intermediate node is located in $B\}$ occurs. Since the nodes distribution is assumed to be uniform, this node could be located anywhere in F with the same probability. Therefore, the probability that this node is located in any area $\Omega \subset F$ is nothing but the ratio of Ω to F. Consequently, $F_{Z|X}(z)$ is given by

$$F_{Z|X}\left(z\right) = \left(1 - \frac{A}{F}\right)^M. \quad (12)$$

Using similar steps to derive A, it can be shown that

$$F = Tc_k^2\left(\theta - \frac{\sin(2\theta)}{2}\right) + Tc_j^2\left(\theta' - \frac{\sin(2\theta')}{2}\right). \quad (13)$$

Finally, the EHP is derived by substituting (12) in (8). Note that the main drawback of Approach 2 is that the EHP depends on the number of potential intermediate nodes M which should be determined by training, i.e., at the cost of larger overhead and lower power efficiency. It is also noteworthy that the so-obtained EHP using either Approach 1 or Approach 2, depends on the transmission capabilities of the k-th and j-th nodes. This is in contrast with the EHP expressions developed so far in the literature. In the next section, based on the the so-obtained EHP and MLH, we propose a novel range-free localization algorithm tailored for heterogeneous wireless sensors networks.

V. The proposed algorithm

In this section, a novel two-step localization algorithm is proposed. In the first step, the k-th anchor broadcasts through the network a packet which consists of a packet header followed by a data payload. The packet header contains the anchor ID as well as its position (x_k, y_k), while the data payload contains its corresponding transmission capability Tc_k. If the packet is successfully received by a node, the latter stores it in its database, then, adds its own transmission capability to the end of the data payload and rebroadcasts the resulting packet. Once this packet is received by another node, its database information is checked. If the k-th anchor information exists and the length of the corresponding stored packet is larger than that of the received one, the node updates the k-th anchor's information', then broadcasts the resulting packet after adding its transmission capability to it. Otherwise, the node discards the received packet. However, when the node is oblivious to the k-th anchor position, it adds this information to its database and forwards the received packet after adding its transmission capability to its end. This mechanism will continue until each regular node in the network becomes aware of all anchors' positions and the transmission capabilities of all intermediate nodes lying between it and each anchor.

Using this information, the $(i - N_a)$-th regular node (or the i-th node) computes then an estimate of its distance to the k-th anchor as

$$\hat{d}_{k-i} = \sum_{l=k}^{k+L-1} h\left(Tc_l, Tc_{l+1}\right) + h^{\text{last}}(Tc_{k+L}). \quad (14)$$

In (14), we assume for simplicity, yet without loss of generality, that L intermediate nodes exist over the shortest path between the k-th anchor and the $(i - N_a)$-th regular node and that the l-th intermediate node is the $(k + l)$-th node. Using $\hat{d}_{k-i}$, $k = 1 \ldots N_a$, the $(i - N_a)$-th regular node is now able to compute an initial guess $(\hat{x}_i, \hat{y}_i)$ of its 2-D coordinates by performing trilateration [20], provided that $N_a \ge 3$.

Unfortunately, errors are expected to occur when estimating the distance between each regular node-anchor pair, thereby hindering localization accuracy. In the second step, we propose to minimize the aforementioned errors. Let ϵ_{ik} denotes the estimation error of the distance between the k-th anchor and the i-th regular node as

$$\epsilon_{ik} = \hat{d}_{k-i} - d_{k-i}, \quad (15)$$

where d_{k-i} is the true distance between the two nodes. As discussed above, this error hinders localization accuracy. As such, we have

$$\begin{cases} x_i = \hat{x}_i + \delta_{x_i} \\ y_i = \hat{y}_i + \delta_{y_i} \end{cases}, \quad (16)$$

where δ_{x_i} and δ_{y_i} are the location coordinates' errors to be determined. Exploiting the Taylor series expansion and retaining the first two terms, the following approximation holds:

$$d_{k-i} \approx d^{\dagger}_{k-i} + \alpha_{k1}\delta_{x_i} + \alpha_{k2}\delta_{y_i}, \quad (17)$$

where

$$d^{\dagger}_{k-i} = \sqrt{\left(\hat{x}_i - x_k\right)^2 - \left(\hat{y}_i - y_k\right)^2} \quad (18)$$

and

$$\alpha_{k1} = \left.\frac{\partial d^{\dagger}_{k-i}}{\partial x}\right|_{\hat{x}_i, \hat{y}_i} = \frac{\hat{x}_i - x_k}{\sqrt{\left(\hat{x}_i - x_k\right)^2 - \left(\hat{y}_i - y_k\right)^2}} = \frac{\hat{x}_i - x_k}{d^{\dagger}_{k-i}}, \quad (19)$$

$$\alpha_{k2} = \left.\frac{\partial d^{\dagger}_{k-i}}{\partial y}\right|_{\hat{x}_i, \hat{y}_i} = \frac{\hat{y}_i - y_k}{\sqrt{\left(\hat{x}_i - x_k\right)^2 - \left(\hat{y}_i - y_k\right)^2}} = \frac{\hat{y}_i - y_k}{d^{\dagger}_{k-i}}, \quad (20)$$

for $k = 1, 2, \ldots, N_a$. Note that $d^{\dagger}_{k-i}$ is different from $\hat{d}_{k-i}$ due to the error incurred by trilateration [20]. Therefore, rewriting (17) in a matrix form yields

$$\boldsymbol{\Gamma}_i \boldsymbol{\delta}_i = \boldsymbol{\zeta}_i - \boldsymbol{\epsilon}_i, \quad (21)$$

where

$$\mathbf{\Gamma_i} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \\ \vdots & \vdots \\ \alpha_{N_a 1} & \alpha_{N_a 2} \end{bmatrix} = \begin{bmatrix} \frac{\hat{x}_i - x_1}{d^{\dagger}_{i-1}} & & \frac{\hat{y}_i - y_1}{d^{\dagger}_{i-1}} \\ \frac{\hat{x}_i - x_2}{d^{\dagger}_{i-2}} & & \frac{\hat{y}_i - y_2}{d^{\dagger}_{i-2}} \\ \vdots & \vdots & \vdots \\ \frac{\hat{x}_i - x_m}{d^{\dagger}_{i-N_a}} & & \frac{\hat{y}_i - y_m}{d^{\dagger}_{i-N_a}} \end{bmatrix}, \tag{22}$$

$$\boldsymbol{\zeta}_i = \begin{bmatrix} \hat{d}_{i-1} - d^{\dagger}_{i-1} \\ \hat{d}_{i-2} - d^{\dagger}_{i-2} \\ \vdots \\ \hat{d}_{i-N_a} - d^{\dagger}_{i-N_a} \end{bmatrix}, \tag{23}$$

$\boldsymbol{\epsilon}_i = [\epsilon_{i1}, \epsilon_{i2}, \ldots, \epsilon_{iN_a}]^T$, and $\boldsymbol{\delta}_i = [\delta_{x_i}, \delta_{y_i}]^T$.

Many methods such as the weighted least squares (WLS) might be used to properly derive $\boldsymbol{\delta}_i$. Using WLS, the solution of (21) is given by :

$$\boldsymbol{\delta}_i = \left(\mathbf{\Gamma}_i^T \mathbf{P}_i^{-1} \mathbf{\Gamma}_i\right)^{-1} \mathbf{\Gamma}_i^T \mathbf{P}_i^{-1} \boldsymbol{\zeta}_i, \tag{24}$$

where $\mathbf{P}_i$ is the covariance matrix of $\boldsymbol{\epsilon}_i$. Since ϵ_{ik} $k = 1, \ldots, N_a$ are independent random variables, $\mathbf{P}_i$ boils down to diag$\left\{\sigma^2_{i1}, \ldots, \sigma^2_{iN_a}\right\}$ where $\sigma^2_{ik} = \sum_{l=k}^{k+L-1} \mathrm{Var}\left\{d_{l-(l+1)}\right\} + \mathrm{Var}\left\{d_{(k+L)-i}\right\}$ is the variance of ϵ_{ik} with $\mathrm{Var}\left\{d_{(k+L)-i}\right\} = \frac{Tc^2_{k+L}}{12}$ and

$$\mathrm{Var}\{d_{l-(l+1)}\} = \int_{Tc_l}^{Tc_l + Tc_{l+1}} \left(\alpha_l^2 H(\alpha_l) + \int_{\alpha_l}^{Tc_l} zH(z)dz\right) f_X(x)dx - \left(\int_{Tc_l}^{Tc_l + Tc_{l+1}} \left(\alpha_l H(\alpha_l) + \int_{\alpha_l}^{Tc_l} H(z)dz\right) f_X(x)dx\right)^2, \tag{25}$$

where $H(\star) = 1 - F_{Z|X}(\star)$ and $\alpha_l = x - Tc_{l+1}$.

A straightforward inspection of (24) and (25) reveals that $\boldsymbol{\delta}_i$ solely depends on the information locally available at the $(N_a + i)$-th regular node and, therefore, is locally computable at this node and does not require any additional information exchange between nodes. Moreover, since $\mathbf{\Gamma}_i^T \mathbf{P}_i \mathbf{\Gamma}_i$ is a 2-by-2 matrix, the entries of its inverse can be analytically and easily derived. Thus, the computation of $\boldsymbol{\delta}_i$ does not burden neither the implementation complexity of the proposed algorithm nor the overall cost of the network.

Once we get $\boldsymbol{\delta}_i$, the value of $(\hat{x}_i, \hat{y}_i)$ is updated as $\hat{x}_i = \hat{x}_i + \delta_{x_i}$ and $\hat{y}_i = \hat{y}_i + \delta_{y_i}$. The computations are repeated until δ_{x_i} and δ_{y_i} approach zero. In such a case, we have from (16) that $x_i \approx \hat{x}_i$ and $y_i \approx \hat{y}_i$ and, hence, more accurate localization is performed.

VI. Simulations Results

In this section, we evaluate the performance of the proposed algorithm in terms of localization accuracy by simulations using Matlab. These simulations are conducted to compare, under the same network settings, the proposed algorithm with some of the best representative range-free methods currently available in the literature, i.e., DV-Hop [11], LEAP [13] and EPHP [14]. All simulation results are obtained by averaging over 100 trials. In this simulations, nodes are uniformly deployed in a 2-D square area $S = 50 * 50\ m^2$. As an evaluation criterion, we propose to use the normalized root mean square error (NRMSE) defined as follows

$$e = \frac{\sum_{i=1}^{N_u} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N_u Tc_i}. \tag{26}$$

We assume that we have only two different transmission capabilities $Tc^{(1)}$ and $Tc^{(2)}$ distributed with the same proportions. This means that the transmission capabilities of 50% of the nodes are equal to $Tc^{(1)}$ while those of the other 50% are equal to $Tc^{(2)}$. In the first two simulations, $Tc^{(1)}$ and $Tc^{(2)}$ are set to $8\ m$ and $14\ m$, respectively. In the last simulation, $Tc^{(1)}$ is fixed and $Tc^{(2)}$ is increased to investigate the robustness of the proposed algorithm.

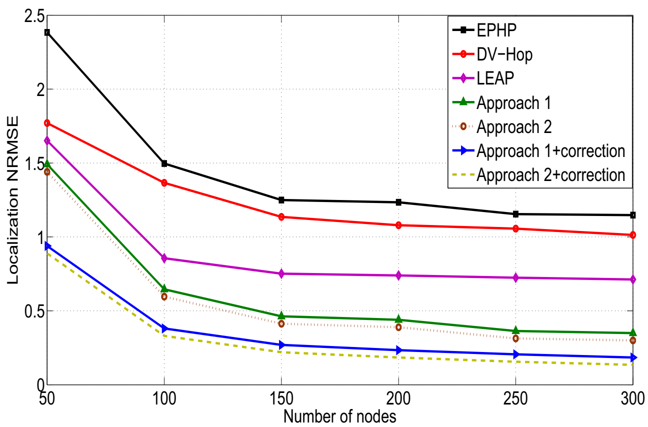

Fig. 4. Localization NRMSE vs. number of nodes.

Fig. 4 plots the localization NRMSE achieved by DV-Hop, EPHP, LEAP and the proposed algorithm for different numbers of nodes N. As can be shown from this figure, the proposed algorithm, with or without localization correction, always outperforms its counterparts. Indeed, our proposed algorithm turns out to be until about three, four and five times more accurate than LEAP, DV-Hop, and EPHP, respectively. Furthermore, from this figure, the proposed algorithm is more efficient if Approach 2 is used to derive the EHP. This is hardly surprising since $Tc^{(1)}$ and $Tc^{(2)}$ are relatively large and, hence, the accuracy of Approach 1 is deteriorated.

Fig. 5 illustrates the localization NRMSE's CDF. Using the proposed algorithm, 94.5% (95% with Approach 2) of the regular nodes could estimate their position within half of the transmission range. In contrast, 49% of the nodes achieve the same accuracy with LEAP, about 29% with DV-Hop, and only 20% with EPHP. This further proves the efficiency of the proposed algorithm.

Figs. 6 shows the localization NRMSE for different deviations between the transmission capabilities $Tc^{(1)}$ and $Tc^{(2)}$. As it can be observed from this figure, the proposed algorithm

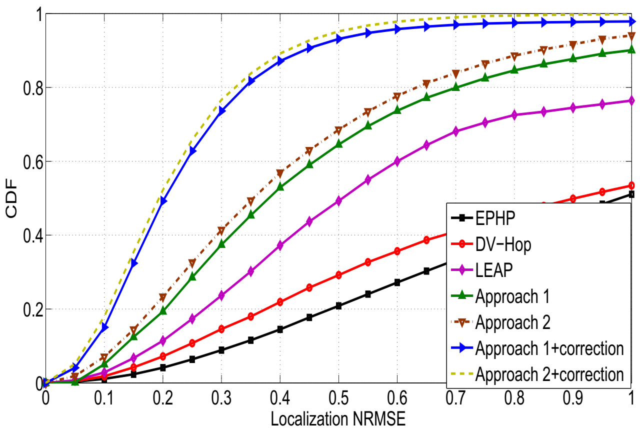

Fig. 5. Localization NRMSE's CDF.

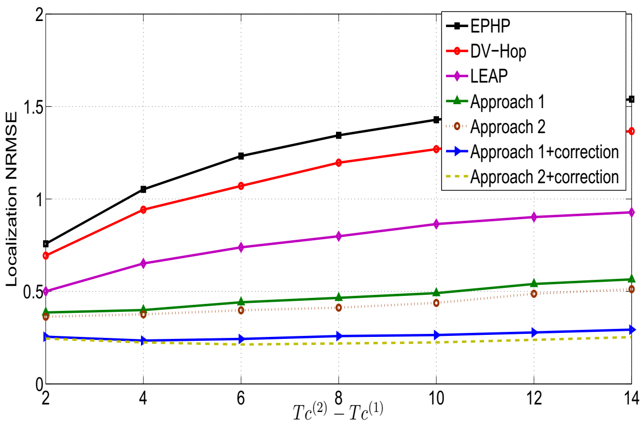

Fig. 6. Localization NRMSE vs. deviation between transmission capabilities.

outperforms its counterparts for any values of $Tc^{(1)}$ and $Tc^{(2)}$. From Fig. 6, the performance of the other benchmark algorithms substantially deteriorates as the difference between $Tc^{(1)}$ and $Tc^{(2)}$ increases while the proposed algorithm performance remains stable. This is expected since the EHP used in our algorithm accounts for the heterogeneity of the WSN, in contrast to the previous ones. Moreover, from this figure, if Approach 1 is used to compute the EHP, the proposed algorithm's efficiency decreases when $Tc^{(2)}$ increases. This collaborates the discussion in Section IV.

VII. Conclusion

In this paper, a novel range-free localization algorithm which accounts for the heterogeneity of WSNs was proposed. Two different approaches were developed to accurately derive the expected hop progress (EHP). It was proven that the obtained EHP depends solely on the information locally available at each node and, hence, can be computed in a localized manner. Furthermore, a localization correction mechanism suitable for heterogeneous WSNs was developed. We showed that the proposed algorithm, whether with or without correction, outperforms in accuracy the most representative range-free localization algorithms in the literature.

References

[1] W. Zhang and G. Cao, "DCTC: Dynamic Convoy Tree-Based Collaboration for Target Tracking in Sensor Networks," *IEEE Trans. Wireless Comm.,* vol. 3, no. 5, pp. 1689-1701, Sept. 2004.

[2] F. Gustafsson and F. Gunnarsson, "Mobile Positioning Using Wireless Networks: Possibilities and Fundamental Limitations Based on Available Wireless Network Measurements," *IEEE Signal Process. Magazine,* vol. 22, no. 4, pp. 41-53, July 2005.

[3] D.P. Agrawal and Q.-A. Zeng, *Introduction to Wireless and Mobile Systems,* 3^{rd} edition CL-Engineering June 2010.

[4] N. Patwari, A. O. Hero III, M. Perkins, N. S. Correal, and R. J. ODea, "Relative Location Estimation in Wireless Sensor Networks," *IEEE Trans. Signal Process.,* vol. 51, no. 8, pp. 2137-2148, August 2003.

[5] D. Niculescu and B. Nath, "Ad Hoc Positioning System (APS) Using AOA," *IEEE INFOCOM'2003,* San Francisco, vol. 3, pp. 1734-1743, March 2003.

[6] H. Ren and M. Q.-H. Meng, "Power Adaptive Localization Algorithm for Wireless Sensor Networks Using Particle Filter," *IEEE Trans. Vehicular Techno.,* vol. 58, no. 5, pp. 2498-2508, June 2009.

[7] X. Cheng, H. Shu, Q. Liang, and D. H-C. Du, "Silent Positioning in Underwater Acoustic Sensor Networks," *IEEE Trans. Vehicular Techno.,* vol. 57, no. 3, pp. 1756-1766, May 2008.

[8] Q. Xiao, B. Xiao, J. Cao, and J. Wang,"Multihop Range-Free Localization in Anisotropic Wireless Sensor Networks: A Pattern-Driven Scheme," *IEEE Trans. on Mobile Comp.,* vol. 9, no. 11, pp. 1592-1607, November 2010.

[9] Z. Ziguo and T. He,"RSD: A Metric for Achieving Range-Free Localization beyond Connectivity," *IEEE Trans. Parallel and Distributed Sys.,* vol. 24, no. 11, pp. 1943-1951, November 2011.

[10] J. Lee, B. Choi, and E. Kim, "Novel Range-Free Localization Based on Multidimensional Support Vector Regression Trained in the Primal Space," *IEEE Trans. on Neural Networks and Learning Systems,* vol. 24, no. 7, pp. 1099-1113, July 2013.

[11] D. Niculescu and B. Nath, "DV Based Positioning in Ad Hoc Networks," *J. Telecomm. Systems,* vol. 22, no. 4, pp. 267-280, 2003.

[12] J-P. Sheu, P-C. Chen, and C.-S. Hsu, "A Distributed Localization Scheme for Wireless Sensor Networks with Improved Grid-Scan and Vector-Based Refinement," *IEEE Trans. Mobile Comp.,* vol. 7, no. 9, pp. 1110-1123, September 2008.

[13] Y. Wang, X. Wang, D. Wang, and D. P. Agrawal, "Range-Free Localization Using Expected Hop Progress in Wireless Sensor Networks," *IEEE Trans. Parallel and Distributed Sys.,* vol. 25, no. 10, pp. 1540-1552, October 2009.

[14] L. Kleinrock and J. Silvester,"Optimum Transmission Radii for Packet Radio Networks or Why Six is a Magic Number," *in Proc. IEEE Nat. Telecommun. Conf.,* pp. 4.3.14.3.5, 1978.

[15] J. C. Kuo, and W. Liao,"Hop Count Distribution of Multihop Paths in Wireless Networks With Arbitrary Node Density: Modeling and Its Applications," *IEEE on Trans. Vehicular Technology,* vol. 56, no. 4, pp. 2321-2331, July 2007.

[16] J.C. Kuo, W. Liao and T.C. Hou,"Impact of Node Density on Throughput and Delay Scaling in Multi-hop Wireless Networks," *IEEE on Trans. Wireless Commun.,* vol. 8, no. 10, pp. 5103-5111, October 2009.

[17] B. Xiao, L. Chen, Q. Xiao and M. Li, "Reliable Anchor-Based Sensor Localization in Irregular Areas," *IEEE Trans. on Mobile Comp.,* vol. 9, no. 1, pp. 60-72, Janvier 2010.

[18] S. Zhang, J. Cao, L. Chen, and D. Chen, "Accurate and Energy-Efficient Range-Free Localization for Mobile Sensor Networks," *IEEE Trans. on Mobile Comp.,* vol. 9, no. 6, pp. 897-910, June 2010.

[19] D. Ma, M. J. Er, and B. Wang, "Analysis of Hop-Count-Based Source-to-Destination Distance Estimation in Wireless Sensor Networks With Applications in Localization," *IEEE Trans. Vehicular Techno.,* vol. 59, no. 6, pp. 2998-3011, July 2010.

[20] D. E. Manolakis, "Efficient Solution and Performance Analysis of 3-D Position Estimation by Trilateration," *IEEE Trans. Aerospace and Electonic Sys.,* vol. 32, no. 4, pp. 1239-1248, October 1996.

[21] C. Bettstetter, "On The Connectivity of Wireless Multihop Networks With Homogeneous and Inhomogeneous Range Assignment, "*Proc. IEEE VTC'2002-Fall,* vol. 3, pp. 1706-1710, 2002.

[22] C. Bettstetter, "On the Connectivity of Ad Hoc Networks," *The Computer Journal,* vol. 47, no. 4, pp.432-447, 2004