Accurate Sensors Localization in Underground Mines or Tunnels

Ahmad El Assaf*, Slim Zaidi*, Sofiène Affes*†, and Nahi Kandil*†
*INRS-EMT, Université du Québec, Montreal, QC, H5A 1K6, Canada, Email: {elassaf,zaidi,affes}@emt.inrs.ca
†LRTCS, University of Quebec in Abitibi-Témiscaming, Rouyn-Noranda, QC, J9X 5E4, Canada, Email: nahi.kandil@uqat.ca

***Abstract*—In this paper, a novel localization algorithm tailored for underground mines is proposed. Using the proposed algorithm, each regular (i.e position-unaware) node estimates its distances to the anchor (i.e., position-aware) nodes exploiting only its locally available information. Furthermore, a new hop count adjustment scheme, which complies with the labyrinthic nature of underground mines, is developed to ensure an accurate distance estimation, thereby making our localization algorithm more precise. Simulations show that our proposed algorithm, consistently outperforms in underground mines the best representative localization algorithms currently available in the literature in terms of accuracy, even with the presence of radiation irregularities.**

***Index Terms*—Wireless sensor networks, localization algorithms, underground mines/tunnels, range-free.**

I. Introduction

Underground mines are typically extensive labyrinths which consist of a very-long main tunnel and several narrow side branches. Such mines often employ hundreds of miners working under extreme environmental conditions. To ensure their safety, efficient and continuous mine monitoring is crucial. This is usually done by analyzing critical information such as the presence and concentration of flammable and toxic gases and dust, the structural integrity and stability of the mine tunnels and water ingress, etc. Due to to their reliability, low cost, and ease of deployment, wireless sensor networks (WSN)s are often envisaged in underground mine to collect and forward such information to an access point (AP). However, the received data at the latter are often fully or partially meaningless if the location from where they have been measured is unknown [1]-[3], making the nodes' localization an essential task in WSNs. Designed to comply with such networks, many localization algorithms exist in the literature [4]-[20]. To properly localize each regular or position-unaware node, most of these algorithms require the distance between the latter and at least three position-aware nodes called hereafter anchors. Since it is very likely in multi-hop WSNs that some regular nodes be unable to directly communicate with all anchors, the distance between each anchor-regular nodes pair is usually estimated using their shortest path. The latter is obtained by summing the distances between any consecutive intermediate nodes located on the shortest path between the two nodes. Depending on the process used to estimate these distances, localization algorithms may fall into three categories: measurement-based, heuristic, and analytical [4]-[20].

Work supported by the CRD, DG, and CREATE PERSWADE <www.create-perswade.ca> Programs of NSERC and a Discovery Accelerator Supplement Award from NSERC.

Measurement-based algorithms exploit the measurements of the received signals' characteristics such as the received signal strength (RSS) [4]-[5] or the time of arrival (TOA) [6], etc. Using the RSS measurement, the distance between any sensors' pair could be obtained by converting the power loss due to propagation from a sensor to another based on some propagation laws. Unfortunately, due the probable presence of noise and interference in underground mines, the distance's estimate would be far from being accurate, thereby leading to unreliable localization accuracy. Using the TOA measurement, nodes require high-resolution clocks and extremely accurate synchronization between them. While the first requirement may dramatically increase the cost and size of sensor nodes, the second results in severe depletion of their power due to the additional overhead required by such a process. Furthermore, due to the presence of noise and/or multipath in underground mines, the TOA measurement is severely affected thereby hindering nodes' localization accuracy.

As far as heuristic algorithms [7]-[8] are concerned, most of them are based on variations of DV-Hop [7]-[8] whose implementation in WSNs requires the computation of the expected hop progress (EHP) (i.e., average distance between any two consecutive intermediate nodes) h_{av} to estimate the distance between a sensor and an anchor as $n_h h_{\mathrm{av}}$ where n_h is the number of hops between the two nodes. Such algorithms have, however, a major drawback. Indeed, h_{av} is computed in a non-localized manner and broadcasted in the network by each anchor. This causes an undesired prohibitive overhead and power consumption, thereby increasing the overall cost of the localization process.

Popular alternatives, more suitable for sensors localization in underground mines, are the analytical-type algorithms [9]-[20] which evaluate theoretically h_{av} using the statistical characteristics of the network deployment. The obtained h_{av} is actually locally computable at each regular node, thereby avoiding the unnecessary overhead and power consumption that would have been incurred if it were broadcasted in the network as in heuristic algorithms. In spite of their valuable contributions, the above algorithms do not provide sufficient accuracy in underground mines due to large errors occurring when mapping the hops into distance units. Indeed, in such mines, it is very likely that the shortest path between an anchor and a regular node be curved, thereby resulting in

978-1-4673-6555-0/15/$31.00 ©2015 IEEE

overestimation of the distance between these two nodes.

In this paper, a novel analytical localization algorithm tailored for underground mines is proposed. Using the proposed algorithm, each regular node estimates its direct distances to the anchors exploiting only its locally available information. Furthermore, a new hop-count adjustment scheme, which complies with the labyrinthic nature of underground mines, is developed to ensure an accurate distance estimation, thereby making our localization algorithm more precise. Simulations show that our algorithm, consistently outperforms in underground mines the best representative localization algorithms currently available in the literature in terms of accuracy.

The rest of this paper is organized as follows: Section II describes the network model. Section III proposes a novel localization algorithm while Section IV and V introduce a novel distance estimation technique and new hop-count adjustment strategy. Simulation results are discussed in Section VI and concluding remarks are made in section VII.

II. Network model

Fig. 1 reproduces the map of the CANMET underground mine[1] in Val-d'Or, Québec, Canada where a network of N uniformly distributed WSN nodes is deployed [10]. All nodes are assumed to have the same transmission capability (i.e., range) denoted by R. Each node is able to directly communicate with any other node located in the disc having that node as a center and R as a radius, while it communicates in a multi-hop fashion with the nodes located outside. 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 triangles and the regular ones are marked with blue dots. Let N_a and $N_u = N - N_a$ denote the number of anchors and regular nodes, respectively. 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.

III. Proposed localization algorithm

As a first step of any anchor-based localization algorithm, the k-th anchor broadcasts through the network a message containing (x_k, y_k, n) where n is the hop-count value initialized to one. When a node receives this message, it stores the k-th anchor position as well as the received hop-count $n_k = n$ in its database, adds one to the hop-count value and broadcasts the resulting message. Once this message is received by an another node, its database information is checked. If the k-th anchor information exists and the received hop-count value n is smaller than the stored one n_k, the node updates n_k to n, increases it by 1, then broadcasts the resulting message. If n_k is smaller than n, the node discards the received message

[1]Please note that the CANMET's map is only taken as a practical example. The proposed algorithm is actually suitable for any other confined environments having topologies formed by tunnels (including underground mines, subway tunnels, city sewage networks, city water distribution networks, etc.).

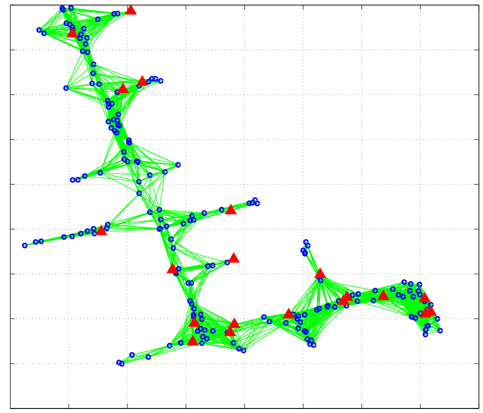


Fig. 1. Network model.

[13]. 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 increasing n by 1. This mechanism will continue until all nodes become aware of all anchors' positions and their corresponding minimum hop-counts. These information are used to estimate the distances between all anchor and regular nodes. Exploiting their available distances' estimates, the latter finally compute their positions by performing multilateration [17].

IV. Distance estimation technique

It is obvious that an efficient distance estimation technique is crucial to guarantee an accurate node localization. In this paper, we propose to directly (i.e., without recurring to the distances between consecutive intermediate nodes) estimate the distance d_{k-i} between the k-th anchor and the i-th regular node. This allows to avoid the cumulative distance estimation error incurred by EHP-based localization algorithms [7]-[20]. In fact, such an error, which has a detrimental effect on localization accuracy, increases with n_k and may become prohibitive in underground mines due to their very-long main galleries.

It has been shown that the minimum mean square error (MMSE) of the distance estimation is obtained if

$$\hat{d}_{k-i} = \mathrm{E}\{Z|n_k\} \tag{1}$$

where $\hat{d}_{k-i}$ is the distance estimate and Z is the random variable that represents the distance d_{k-i}. In order to derive $\mathrm{E}\{Z|n_k\}$, we start by deriving the conditional cumulative distribution function (CDF) $F_{Z|n_k}(z|n_k)$ of Z with respect to n_k. As could be observed from Fig. 2, $Z \leq z$ is guaranteed only if there are no nodes in the area

$$A_z = S(k, \theta, hR) - S(k, \theta, z) \tag{2}$$

with $S(\star, \theta, x)$ is the sector having the $\star$-th node as a center, θ as an angle, and x as a radius. $F_{Z|n_k}(z|n_k)$ can be then defined as

$$F_Z(z)\,(z|n_k) = P\,(Z \leq z|n_k) = P\,(\mathrm{E})\,, \tag{3}$$

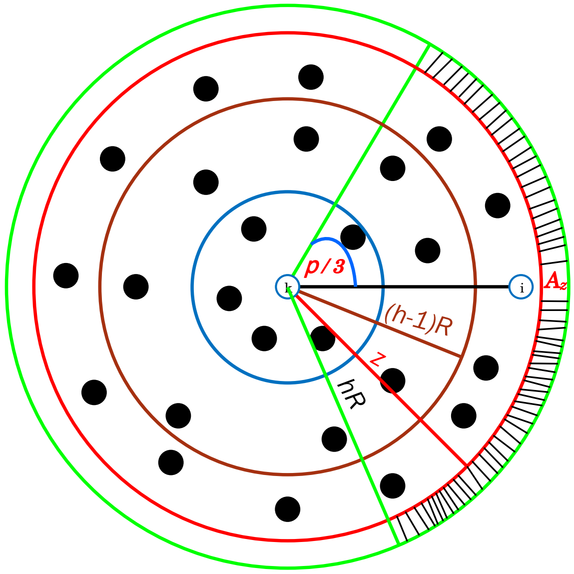


Fig. 2. Distance analysis.

where $P(\mathrm{E})$ is the probability that the event $\mathrm{E} = \{$no nodes in the area $A_Z\}$ occurs.

Since the nodes are uniformly deployed in the CANMET experimental mine (cf. Fig. 1), the probability of having K nodes in A_z follows a Binomial distribution $\mathrm{Bin}\,(N, p)$ where $p = \frac{A_z}{S}$ and S is the total CANMET'S surface . 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 $\mathrm{Pois}(\lambda A_z)$ where $\lambda = N/S$ is the average nodes density in the network [19]. Consequently, for a large number of nodes N and small p, we have

$$F_{Z|n_k}\left(z|n_k\right) = e^{-\lambda A_z}. \tag{4}$$

It can be readily shown from (2) that

$$A_z = \frac{\pi}{3}\left(h^2R^2 - z^2\right), \tag{5}$$

and, hence, $\hat{d}_{k-i}$ is given by

$$\begin{aligned}\hat{d}_{k-i} =& R\Big(n_k - (n_k - 1)\, e^{-\frac{\lambda\pi R^2}{3}(2n_k-1)}\Big) - e^{-\frac{\lambda\pi R^2}{3}h^2}\int_{\left(n_k-1\right)R}^{n_k R} e^{\frac{\lambda\pi}{3}z^2} dz\\ =& \frac{\sqrt{3}}{2\sqrt{\lambda}}\left(\mathrm{Erfi}\left(\mathrm{n_k R}\sqrt{\frac{\lambda\pi}{3}}\right) - \mathrm{Erfi}\left((\mathrm{n_k}-1)\mathrm{R}\sqrt{\frac{\lambda\pi}{3}}\right)\right)\times\\ & e^{-\frac{\lambda\pi n_k^2 R^2}{3}} + R\left(n_k - \left(n_k - 1\right)e^{-\frac{\lambda\pi R^2}{3}\left(2n_k-1\right)}\right),\end{aligned} \tag{6}$$

where $\mathrm{Erfi}(\mathrm{x})$ is the imaginary error function. A straightforward inspection of (6) reveals that $\hat{d}_{k-i}$ depends solely on information locally available at the i-th regular node and, hence, its computation does not require any additional overhead or power cost. Such a feature is actually suitable for WSNs wherein power is a scarce resource.

V. Hop-count adjustment

Due to the labyrinthic nature of underground mines, it is very likely that the shortest paths between one regular node and some anchors are not straight lines. This unfortunately leads to an overestimation of the distances between these nodes, when mapping the number of hops into distances, thereby hindering the localization accuracy. In order to overcome this, former works have developed anchor selection mechanisms aiming to select only the anchors which do not fall in the above undesired situation. Despite their valuable contributions, such mechanisms require a large number of anchors to ensure the proper node localization, which may significatively increase the overall cost of the WSN. Furthermore, using these mechanisms, each regular node locates itself using a reduced number of anchors, thereby deteriorating its localization accuracy. In this paper, we propose to adjust the hop-count value of each anchor which falls in an undesired situation. This makes the regular node benefit from all the available anchors in the network.

Algorithm 1 Localization algorithm for anchor nodes

```
% k refers to the k-th anchor node %
s_k = {}
for j=1 to N_a and j ≠ k do
    w_j ← Eq. (7)
    s_k = s_k ∪ {w_j}
end for
Broadcast the set s_k of anchors weights
```

Algorithm 2 Localization algorithm for regular nodes

```
% i refers to the i-th regular node %
% s_{k_i} is the set of the anchors weights at the nearest anchor node from the i-th regular node%
for k=1 to N_a do
    n_k^stored = n_k
    n_k = n_k^stored × w_k
    d̂_{k−i} ← Eq. (6)
end for
% x̂_i, and ŷ_i can be estimated using multilateration. %.
```

After receiving all anchors' information, the k-th anchor becomes aware of the positions of all other anchors in the network and, hence, is able to compute all the true distances separating it from the latter. Since this anchor is also aware of the hop-count value of any other anchor j, it is able to derive the correction weight w_j as

$$w_j = \frac{2\sqrt{\lambda\left(\left(x_k - x_j\right)^2 + \left(y_k - y_j\right)^2\right)}}{n_j\left(2\sqrt{\lambda}R - \sqrt{3}\mathrm{Erfi}\left(\sqrt{\frac{\lambda\pi}{3}}\mathrm{R}\right)\mathrm{e}^{-\frac{\lambda\pi \mathrm{R}^2}{3}}\right)}. \tag{7}$$

After computing all its weights, each anchor broadcasts them in the network. A regular node, could then exploits the weights of its nearest anchor to adjust the stored hop-count values by multiplying them by their corresponding weights, and estimate its distances to the anchors using the resulting weights.

Processing steps at the anchors and regular nodes are summarized in algorithms 1 and 2, respectively.

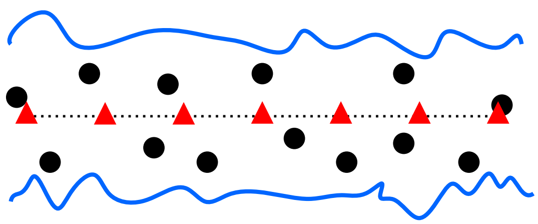
VI. Simulations results

In this section, we evaluate by simulations the performance of the proposed algorithm in terms of localization accuracy using Matlab. These simulations are conducted to compare, under the same network settings, the proposed algorithm with some of the best representative localization algorithms currently available in the literature, i.e., DV-Hop [7], LAEP [9], RAL [18], and pattern-driven [20].

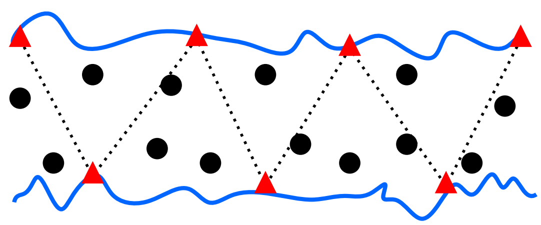
As an evaluation criterion, we propose to use the normalized root mean square error (NRMSE) defined as follows

$$NRMSE = \frac{\sum_{i=1}^{N_u} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N_u R}. \qquad (8)$$

All the following results are obtained by averaging over 200 trials. In all simulations, R and N_a are set to 22 m, and 20, respectively. Two anchor placement strategies are considered: the linear and triangular anchor placements as depicted in Figs. 3(a) and 3(b), respectively.

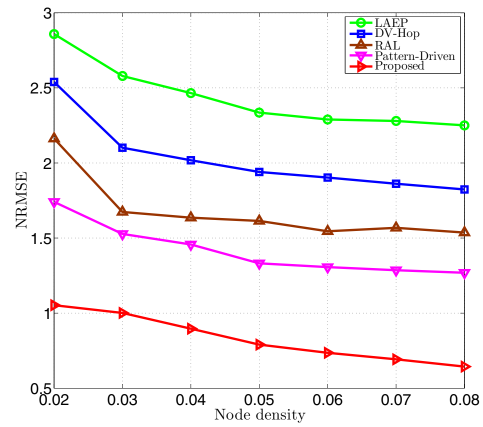


(a) Linear anchor placement.

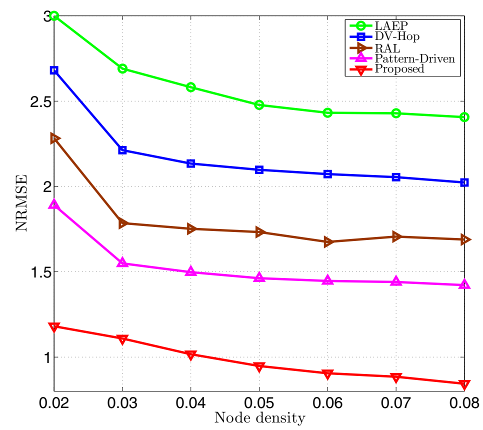


(b) Triangular anchor placement.

Fig. 3. Anchor placement strategies.



(a) Linear anchor placement.



(b) Triangular anchor placement.

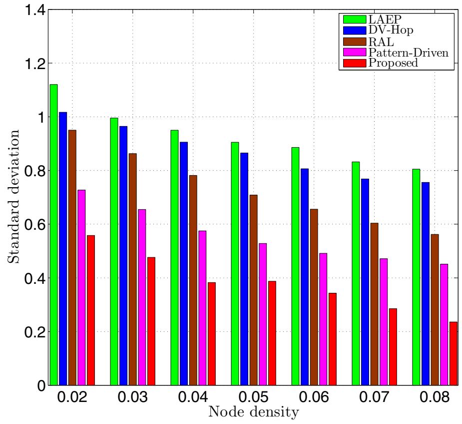
Fig. 4. Localization NRMSE with linear and triangular anchor placement strategies versus λ.

Fig. 4 plots the localization NRMSE achieved by LAEP, DV-Hop, RAL, pattern-driven, and our proposed algorithm versus the node density, for the two anchor placement strategies: linear and triangular. As can be shown from these figures, the proposed algorithm always outperforms its counterparts. Indeed, with the linear anchor placement (triangular anchor placement), it is by about 71% (77%), 65% (72%), 58% (64%), 50% (55%) more accurate than LAEP, DV-Hop, RAL, pattern-driven, respectively.

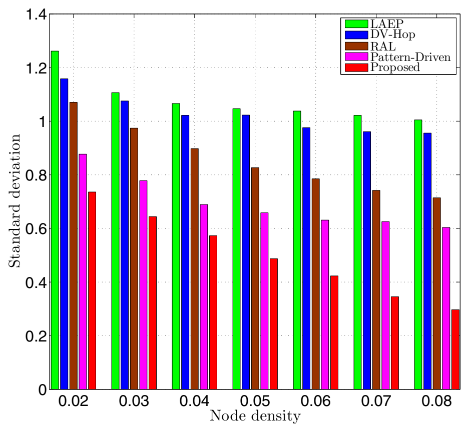
Fig. 5 shows the NRMSEs' standard deviations achieved by all localization algorithms for different node densities, for the two anchor placement strategies: linear and triangular. As can be observed from these figures, regardless of the anchor placement strategy, the one achieved by the proposed algorithm substantially decreases when λ increases while those achieved by the other algorithms slightly decrease. This means that implementing our algorithm in any network topology guarantees an accurate localization for any given realization. This result is very interesting in terms of implementation strategy, since it proves that the result in Fig. 4 becomes more and more meaningful as λ grows large.

Fig. 6 illustrates the localization NRMSE's CDF achieved by our proposed algorithm as well as that achieved by the other algorithms for the two anchor placement strategies: linear and triangular with $\lambda = 0.03$. Using the proposed algorithm, until 70% (62%) of the regular nodes could estimate their position within half of the transmission range in the linear anchor placement case (triangular anchor placement case). In contrast, until 35% (32%), 30% (25%), 20% (18%), and only about 15% (11%) of the nodes achieve the same accuracy with pattern-driven, RAL, DV-Hop, and LAEP respectively. This further proves the efficiency of our new algorithm.

Fig. 7 plots the localization NRMSEs for different numbers of anchors N_a. From this figure, the accuracy of all localization algorithms decreases when N_a increases. This is expected since the trilateration becomes more efficient for large N_a. Moreover, as it can be seen from Fig. 7, the proposed algorithm outperforms its counterparts, and the NRMSE achieved by the proposed algorithm substantially decreases when the number of anchors increases while those achieved by the other algorithms slightly decrease. This is due to the fact that the

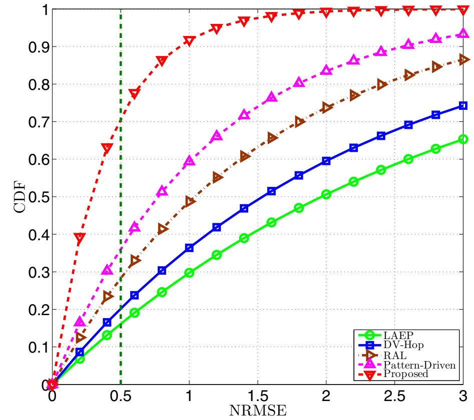


(a) Linear anchor placement.

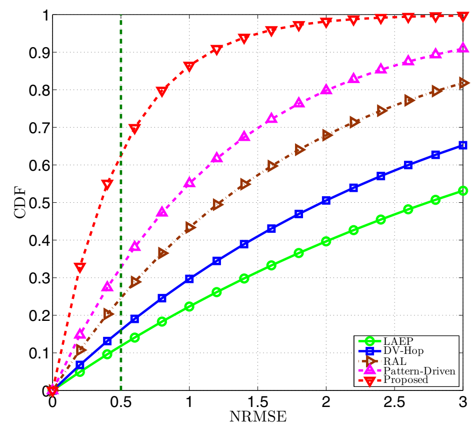


(b) Triangular anchor placement.

Fig. 5. NRMSE's standard deviation with linear and triangular anchor placement strategies versus λ with $N_a = 20$.



(a) Linear anchor placement



(b) Triangular anchor placement.

Fig. 6. NRMSE's CDF achieved by the proposed and other algorithms, with linear and triangular anchor placement strategies when $\lambda = 0.03$.

proposed algorithm becomes more efficient and accurate, since increasing the number of anchors leads to a more precise and accurate weights derivation, and then, more robust hop count adjustment strategy. This further verifies the effectiveness of our proposed algorithm.

Fig. 8 plots the localization NRMSEs achieved by the proposed algorithm and its counterparts versus the degree of range irregularity (DoI), when $\lambda = 0.03$. A range irregularity model similar to that in [21] was implemented. From these figures, the localization NRMSEs achieved by all algorithms deteriorate, as expected, due to the range irregularity. This is expected since these phenomena are not taken into account when designing the proposed algorithm and its counterparts. However, from this figure, the proposed algorithm remains more accurate and robust than its counterparts. Indeed, in contrast with the latter, its achieved NRMSE only slightly deteriorates with DoI, thanks to the developed hop-count adjustment scheme.

VII. Conclusion

In this paper, we proposed a novel analytical localization algorithm tailored for underground mines. Using the proposed algorithm, each regular node estimates its direct distances to the anchors exploiting only its locally available information. We also developed a new hop-count adjustment scheme, which complies with the labyrinthic nature of underground mines, to ensure an accurate distance estimation, thereby making our localization algorithm more precise. Simulations show that our algorithm, consistently outperforms in underground mines the best representative localization algorithms currently available in the literature in terms of accuracy.

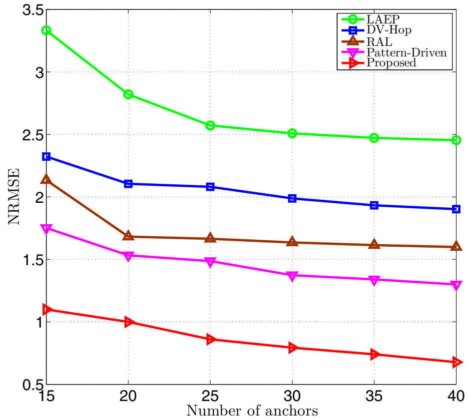
References

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

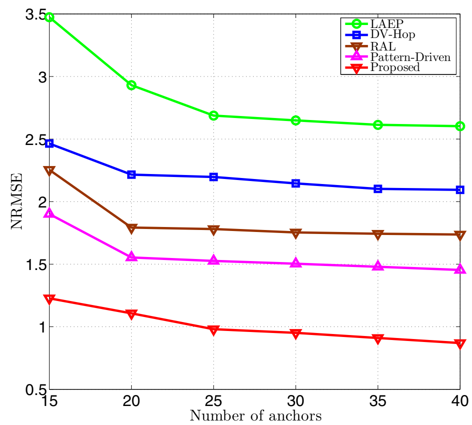
[2] S. Zaidi and S. Affes, "Distributed collaborative beamforming in the presence of angular scattering," *IEEE Trans. Commun.*, vol. 62, pp. 1668-1680, May 2014.

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

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

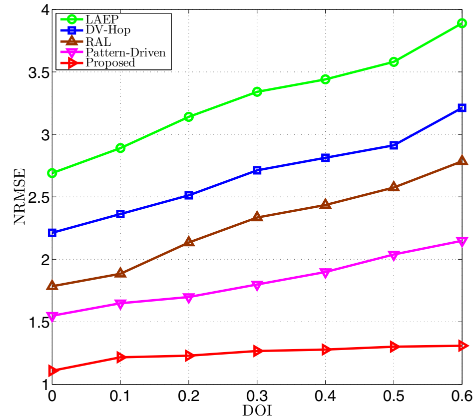


(a) Linear anchor placement

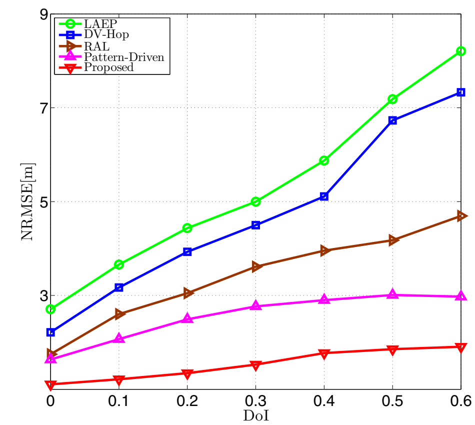


(b) Triangular anchor placement.

Fig. 7. Localization NRMSE vs. anchors number achieved by the proposed and other algorithms, with linear and triangular anchor placement strategies when $\lambda = 0.03$.



(a) Linear anchor placement



(b) Triangular anchor placement.

Fig. 8. Localization NRMSE vs. DoI achieved by the proposed and other algorithms, with linear and triangular anchor placement strategies when $\lambda = 0.03$.

[5] J. Rezazadeh, M. Moradi, A.S. Ismail and E. Dutkiewicz, "Superior Path Planning Mechanism for Mobile Beacon-Assisted Localization in Wireless Sensor Networks," *IEEE Sensors J.,* vol. 14, no. 9, pp. 3052-3064, May 2014.

[6] S. Hong, D. Zhi, S. Dasgupta, and Z. Chunming, "Multiple Source Localization in Wireless Sensor Networks Based on Time of Arrival Measurement," *IEEE Trans. Signal Process.,* vol. 62, no. 8, pp. 1938-1949, February 2014.

[7] D. Niculescu and B. Nath, "Ad hoc positioning system (APS)," *Proc. IEEE GLOBECOM'2001,* San Antonio, TX, USA, November 25-29, 2001.

[8] A. Boukerche, H.A.B.F. Oliveira, E.F. Nakamura, A.A.F. Loureiro, "DV-Loc: a scalable localization protocol using Voronoi diagrams for wireless sensor networks," *IEEE Wireless. Commun. Mag.,* vol. 16, no. 2, pp. 50-55, April 2009.

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

[10] A. El Assaf, S. Zaidi, S. Affes, and N. Kandil, "Efficient Range-Free Localization Algorithm for Randomly Distributed Wireless Sensor Networks," *IEEE GLOBECOM'2013,* Atlanta, GA, December 9-13, 2013.

[11] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Range-free localization algorithm for heterogeneous wireless sensors networks," *IEEE WCNC'2014,* Istanbul, Turkey, Apr. 6-9, 2014.

[12] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Accurate Nodes Localization in Anisotropic Wireless Sensor Networks," *IEEE ICUWB'2015,* Montreal, QC, Canada, October 4-7, 2015.

[13] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Range-free localization algorithm for anisotropic wireless sensor networks," *IEEE VTC'2014-Fall,* Vancouver, Canada, Sep. 14-17, 2014.

[14] Z. Shigeng, C. Jiannong, L.-J. Chen , C. Daoxu Chen, "Accurate and Energy-Efficient Range-Free Localization for Mobile Sensor Networks," *IEEE Trans. Mobile Comput.,* vol. 9, no. 6, pp. 897-910, June 2010.

[15] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Accurate Nodes Localization in Anisotropic Wireless Sensor Networks". *Inter. J. Dist. Sensor Net.*, vol. 2015, pp. 1-17, April 2015.

[16] S. Lee, B. Koo, S. Kim, "RAPS: Reliable Anchor Pair Selection for Range-Free Localization in Anisotropic Networks," *IEEE Commun. Lett.,* vol. 18, no. 8, pp. 1403-1406, July 2014.

[17] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Low-cost localization for multi-hop heterogeneous wireless sensor networks". Accepted for publication in *IEEE Trans. Wireless. commun.*, August 2015.

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

[19] A. EL Assaf, S. Zaidi, S. Affes, and N. Kandil, "Cost-effective and Accurate Nodes Localization in Heterogeneous Wireless Sensor Networks," *IEEE ICC'2015,* London, United Kingdom, June. 8-12, 2015.

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

[21] S. Biaz, Ji. Yiming, Q. Bing, Wu. Shaoen, "Realistic radio range irregularity model and its impact on localization for wireless sensor networks," *IEEE WiCOM'2005,* Wuhan, China, Sept. 23-26 2005.