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RESEARCH ARTICLE

Robust Localization System Using Vector Combination in Wireless Sensor Networks

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ABSTRACT This paper proposes a vector-based localization system that uses both distance and angle information. In wireless sensor networks, the positions of nodes are commonly determined by a range-based localization system using distance information. If both distance and angle information are available, it is possible to improve the accuracy of estimating the positions of nodes compared to a positioning system with only distance information. Existing studies using distance and angle information assume that all the nodes are directly connected to one another and do not consider a method for measuring angle information between the nodes that are not directly connected. However, this assumption may not be valid for real-world wireless sensor networks especially with a large number of nodes having a limited communication range. The proposed localization algorithm solves this problem by a vector combination that transforms the vectors on the local coordinate system to the network-wide global coordinate system. The proposed algorithm is shown to be robust especially even in a network with 1-edge connectivity. Simulation results show that the proposed algorithm has up to 70% higher positioning accuracy compared to the existing iterative range-based algorithm such as MDS-MAP(C,R).

INDEX TERMS Angle of arrival (AOA), distance, localization, positioning, communication range, vector combination, wireless sensor network.

I. INTRODUCTION

The position of nodes is very useful for wireless networks because it allows great opportunities like location-based services and transmit power optimization. The global positioning system (GPS) is currently very popular for positioning, in which the distances between satellites and a receiver are measured and the location of the receiver is estimated by the trilateration method. GPS, however, may not be an effective solution for wireless sensor networks since the signals from satellites do not work indoors and, more importantly, it requires high cost and high power consumption for small devices. Therefore, it is of prime importance to estimate the locations of the nodes more efficiently without GPS. In wireless sensor networks with numerous nodes, it is common that the nodes in the network exchange necessary information, such as distance and connectivity information, and estimate the locations of the nodes by range-based localization algorithms.

Recently, advances in hardware development and wireless communication technology have made it possible to measure the angle of arrival (AOA) of signal and apply it into range-based algorithms in large network scenarios. Accordingly, high positioning performance can be achieved by methods of calculating the position of nodes using angle information. Although most of the existing range-based research uses only distance information or only angle information for estimating the position of nodes, some algorithms for positioning using both distance and angle information are proposed [1]–[4]. The method that uses both information can provide higher positioning accuracy compared to the conventional distance-based methods in exchange for some resource costs (e.g., hardware cost, system complexity, power consumption). Improving node positioning performance through additional resource costs may be considered a good approach, since issues related to cost, complexity, and even power

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consumption can be overcome as technology advances. But it is assumed that the AOA between every single node pair in the network is known or measured in those algorithms. In the real world, however, two nodes can measure AOA only when they are in close proximity (within the communication range), and it is difficult to know the AOA between two nodes that are far away from each other (beyond the communication range). Thus, such an assumption about the full knowledge of all the AOA in the network is not practical and is hardly feasible in large networks.

In addition, for a large network, there are likely to be 1-edge connectivities in some parts of the network. When a network is presented in a graph, it is said to be k-edge connected if and only if it remains connected even after the removal of any $k - 1$ edges [5]. If a network is 1-edge connected, some nodes have only one connected node. In such a case, it is possible to measure the distance between those 1-edge connected nodes, but it is difficult to estimate the location of those nodes because either at least two distances or a distance and an AOA are required to calculate the location of nodes. Since the conventional range-based algorithms usually use either distance or AOA, not both, it is difficult, if not possible, to estimate the location of the nodes in a network with 1-edge connectivity.

Based on the aforementioned motivation, the goal of this paper is to overcome the aforementioned limitations of the conventional localization algorithms in large networks by vector combinations between nodes with both distance and angle information. In practical wireless sensor networks, generally, each node does not have any knowledge of the geographical coordinate system, such as GPS, and only has the AOA information in its local coordinate system due to the cost and power consumption budget of the nodes. Since the AOA information of each node is measured in its local coordinate system, it is necessary to define a network-wide global coordinate system and transform every AOA information in the local coordinate system to the global coordinate system so that the absolute orientation in every AOA information is identified in the global coordinate system. In other words, the proposed algorithm processes the angle information based on the relationship of the local coordinate systems of the nodes to create a global coordinate system. Then, every vector between all nodes in local coordinate systems is transformed to another vector on the global coordinate system by vector combination, in which a new vector can be defined between the nodes that are beyond the communication range. The proposed algorithm is referred to as an enhanced hybrid localization system (EHLS) in this paper. The contributions of this paper are summarized as follows:

1) A hybrid localization algorithm with both distance and angle information is proposed for large networks. Unlike the existing algorithms, the proposed algorithm does not assume that every node in the network is directly connected to each other. Instead, for those nodes that are far beyond the communication range, vector combination is used to find the angle information between the nodes.
2) The proposed algorithm is robust with a high positioning performance especially even in a network with 1-edge connectivity, in which the existing localization algorithms do not work well.
3) An extensive number of simulations are performed to consider multiple nodes distributions, and various amounts of distance and angle measurement errors to analyze the positioning performance of the proposed algorithm for large networks. EHLS can provide up to 70% higher positioning accuracy than the conventional range-based localization method (MDS-MAP(C,R)) [6].

The remainder of this paper is organized as follows: Focusing on the existing localization algorithms, several studies related to this research is introduced in section II. The proposed algorithm is described in detail in section III. The performance results of the comparison between the proposed algorithm and the existing algorithms have shown in section IV. In the last, a simple conclusion is described in section V.

II. RELATED WORKS

The traditional algorithms for range-based localization (e.g., least-squares minimization (LSM), simulated annealing, genetic algorithms) can estimate the position of nodes through iterative calculations using distance information, but the convergence speed is generally very slow or there is a problem of being stuck in the local minima without finding the optimal solution. To mitigate this problem, a multidimensional scaling (MDS)-based localization method is often used to provide a very good starting point to the LSM method [6].

Studies on MDS-based localization systems have been active over the past decade. The most basic MDS method, classical MDS (CMDS) [7], uses the property of the scalar product and eigenvalue decomposition to calculate the position of a node in a matrix of squared distance. It is easy to calculate and can provide a good starting point for all nodes because all information is calculated at once. but, it does not guarantee good positioning performance in irregular topology or large networks because the error of each component expands to the positioning performance error of all nodes. The result of the CMDS method is the relative position of the nodes, and it can be further converted into the absolute position using a linear transformation technique such as procrustes analysis (PA) [8]. Shang applied the MDS-based positioning method even in an environment containing connectivity information instead of measured distance values [6], [9]. He also introduced a general MDS-based calculation method through the MDS-MAP series (i.e., MDS-MAP(C), MDS-MAP(C,R), MDS-MAP(P), MDS-MAP(P,R)). MDS-MAP(C) has the same advantages and disadvantages as CMDS because it is a positioning method similar to CMDS, except that connectivity information can replace distance information.

MDS-MAP(C,R) has the advantage of being able to improve the positioning performance of nodes through repeated calculations, it has the disadvantage of requiring that much calculation time. MDS-MAP(P) which is a method of combining local maps generated by each node has the advantage of showing superior positioning performance compared to MDS-MAP(C) in an irregular network. However, there is a disadvantage in that errors may be accumulated in the process of combining each local map. MDS-MAP(P,R) corrects the incorrectly anticipated location of nodes occurring in the cumulative process through repeated LSM calculations. Since the calculation of the position of each node takes place after updating the location information of its own neighboring nodes, it has the disadvantage of requiring continuous communication between the nodes and lengthening the calculation time.

In order to perform the range-based positioning even in complex network topology, many studies on distributed or cluster-based calculation methods have also been conducted. Stojkoska *et al.* [10], Yu and Wang [11], Shon *et al.* [12], [13] proposed algorithms that divide the network into several clusters and perform calculations based on MDS or triangulation for each cluster, and combine the results later. These studies are a realistic approach to cluster-based localization, but there is a disadvantage in that the cluster map could not be synthesized if the number of gateway nodes was insufficient or an error occurred when selecting the cluster head. Costa *et al.* [14] assumed that each node only knows the distance to the neighboring nodes and introduced a distributed calculation that updates the map through communication with each other. Zhang *et al.* [15] proposed distributed localization system based on MDS-MAP. it can reduce the computational complexity of MDS-MAP of centralized type. These algorithms have the same advantages and disadvantages as the MDS-MAP(P,R) has.

Additionally, there have been studies to improve positioning performance through the prediction of additional information. For range-based algorithms, the distance between the nodes that cannot communicate directly can be estimated by a sum of the distances between the intermediate nodes using shortest path algorithms such as Dijkstra or Floyd. However, since this estimated distance is different from the actual Euclidean distance, there is some performance loss in localization accuracy. To reduce the performance loss, it is necessary to estimate the distance more accurately. Iyengar and Sikdar [16] classified quadrilateral formations and estimated more accurate distances using triangulation. In this method, there is a disadvantage that cannot be applied when the number of gateway nodes is less than two. Jia *et al.* [17] and Wang and Qiu [18] used a heuristic method to estimate the distance and merge local maps created for each cluster. Through this, a method combining local maps was suggested even under insufficient conditions (commonly, $\eta + 1$ number of nodes are required for the positioning system to merge local maps, where η is the number of dimensions of space). But, there is a limitation in that a method of avoiding the accumulation of errors in positions of nodes that occurred in the merging process is not presented.

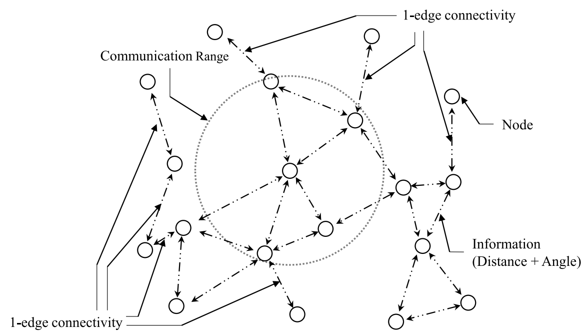

FIGURE 1. Wireless sensor network model with 1-edge connectivity.

Meanwhile, localization algorithms using angle information have also been studied. Ash and Potter [19] proposed a RAST algorithm that calculates the position of a node in a network using only AOA measurements. Watabe [20] devised a node localization system using AOA through a two-step calculation process through the LSM approach. However, these AOA-based algorithms has the limitation that at least each node must have at least two adjacent nodes. In addition, a positioning system using both distance and angle information as an input value was also proposed by Abreu and Destino [1]. This algorithm, referred to as super MDS (SMDS), is a node localization method that estimates vectors using the angle between neighboring nodes and calculates the position of nodes using the vectors. Since then, several SMDS-based studies have been conducted [2]–[4]. These algorithms that use distance and angle information at the same time have high positioning performance than the existing algorithms that use only distance information. And the performance of positioning estimation of those algorithms is closer to or better than the iterative LSM-based method. However, the SMDS-based algorithms require all the angles for every node pair, and it is difficult to know the angle between nodes that are far apart and not directly connected. Due to this limitation, it is practically difficult to implement the SMDS-based algorithm in large networks.

III. PROPOSED ALGORITHM

The main feature of the proposed algorithm is to improve the positioning accuracy by generating vectors between nodes that are not directly connected. The existing hybrid (use both distance and angle information) localization algorithms require distance and angle information between all nodes to generate a kernel matrix for calculating the positions of all nodes [1]–[4]. However, obtaining such information (especially, angle information) between two nodes that are not directly communicated is difficult, if possible. The proposed algorithm calculates distance and angle values by generating vectors between nodes that are not directly connected and calculates the positions of all nodes by reconstructing necessary information in a large network.

Fig. 1 shows the wireless sensor network model with 1-edge connectivity in a two-dimensional space. Some nodes in the network are only connected with one neighboring node, which is called 1-edge connectivity. A large network with a random node distribution is often likely to have 1-edge connectivity around the outermost part of the network. If the communication link at the 1-edge connectivity fails, the connectivity of the whole network is broken and some nodes in the network are unreachable.

It is assumed that the proposed algorithm is applied to the network with the following conditions:

- All nodes have no or little mobility.
- There are one or more routing paths between any pair of nodes in a network.
- Every node can estimate distance and angle values from the neighboring nodes within the communication range.
- The network can have 1-edge connectivity.

There are several reasons to limit the mobility of nodes. Mobility of sensor nodes can lead to the deterioration of the quality of communication links and the failure of data transmission [21]. Also, mobility leads to frequent route changes, and it causes a considerable packet delivery delay. Joins to the network sometimes occur due to their movement, but nodes cannot start transmitting data as soon as they connect to the network. In addition, mobility brings additional effects, such as small-scale fading (e.g., Doppler shift, time variations) [22]. The proposed localization method has three steps: distance and angle estimation, vector combination, and position calculation. The details of each step (how to manufacture the distance and angle information, how to construct vector between nodes, etc.) are described below.

A. DISTANCE AND ANGLE ESTIMATION

This section describes the contents of estimating distance and angle and aligning them for EHLS localization. It consists of three steps: *1)* estimating distance information between neighboring nodes, *2)* transforming every node's local coordinate system to the global coordinate system, and *3)* estimating every node's angle information from neighboring nodes in the global coordinate system.

1) ESTIMATING DISTANCE INFORMATION

Each node calculates the distance value from each neighbor node within its communication range, in which the calculation is often conducted by utilizing signal measurement data such as received signal strength indicator (RSSI) or time of flight (TOF), etc. RSSI technique requires no additional hardware, so it can be applied to almost wireless sensor networks. RSSI technique measures the signal strength decreases as the signal propagates outward from the transmitter. For this reason, RSSI techniques are highly influenced by noise in the environment. TOF technique uses signals that move close to the speed of light, advanced hardware is needed to accurately record the arrival time of wireless signals [23]–[25]. After estimating distance values, it is possible to perform adjustments of distance values for all estimated distance values between neighboring nodes for better performance.

However, the estimated distance between nodes k and l based on the measurement at node k and the estimated distance between the same nodes (nodes k and l) at node l may be slightly different in an actual wireless network. Generally, there is no way to find the accuracy of the sensor in each node, it is difficult to see which estimation is more accurate in practical systems. Thus, an estimated distance value $\hat{d_{kl}}$ is required to take an average by following equations:

$$\hat{d_{kl}} = \begin{cases} \frac{d_{kl}+d_{lk}}{2} & \text{if } (k, l) \in E, \\ \infty & \text{Otherwise,} \end{cases} \tag{1}$$

where E is the set of directly connected node pairs. This procedure of estimating distance values may be simple and common in practical wireless networks.

Note that, in a wireless network, measured distance values contain multiplicative noises which increase in proportion to distance [26]–[28] like the following equation:

$$\rho_{kl} = d_{kl} + d_{kl}N(0, nf^2), \tag{2}$$

where ρ_{kl} and d_{kl} mean the measured distance value and the true distance value, respectively. nf is the distance noise factor.

2) COORDINATE TRANSFORMATION

Since each node measures relative angle information in its local coordinate system, those relative angle values of the nodes can not be simply aligned together. Thus, the relative angle value measured on each local coordinate system requires a coordinate transformation, which is the angle system conversion of each local coordinate to the unified coordinate (global coordinate) system, in order to get the absolute arrival angle on the global coordinate system. In other words, the offset angle value (i.e., orientation) of every local coordinate system with respect to the global coordinate system is estimated and then the relative arrival angle measured on every node's local coordinate system is converted by adding the offset angle value to get the absolute arrival angle on the global coordinate system.

As shown in Fig. 2, angle information consists of orientation information and AOA measurements. The angle values at node k from node l can be represented by the following equation:

$$\theta_{kl} = \phi_{kl} + \alpha_k, \tag{3}$$

where θ_{kl} is the absolute arrival angle at node k from node l on the global coordinate system, ϕ_{kl} is relative arrival angle at node k from node l on the local coordinate system (i.e., AOA measurement), and α_k is the offset angle value (i.e., orientation) of node k on the global coordinate system.

The method of calculating the orientations of nodes is studied in the literature [19], where each orientation of the nodes can be calculated by using a relaying technique. The equations for calculating the set of orientations $\boldsymbol{\alpha} = \{\alpha_m\}^{\mathsf{T}}$ are expressed in (4)-(11). In angular calculations, the modulo 2π angular format is used. First, the set of relative arrival

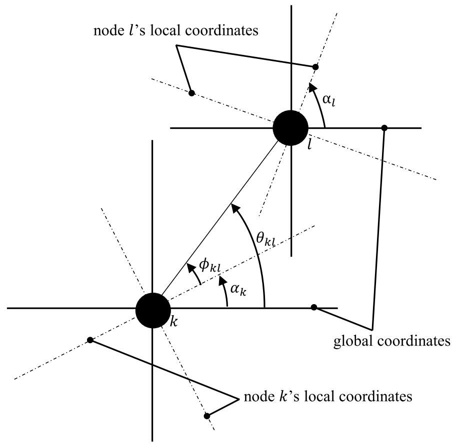

FIGURE 2. Representation of angle information: local coordinate system and global coordinate system.

angles Φ is defined in matrix form as

$$\Phi = \{\boldsymbol{\phi}_m\} = \begin{bmatrix} 0 & \phi_{21} & \phi_{31} & \cdots & \phi_{N1} \\ \phi_{12} & 0 & \phi_{32} & \cdots & \phi_{N2} \\ \phi_{13} & \phi_{23} & 0 & \cdots & \phi_{N2} \\ \vdots & \vdots & & \ddots & \\ \phi_{1N} & & \cdots & \phi_{1N-1} & 0 \end{bmatrix}, \quad (4)$$

where a relative arrival angle ϕ_{kl} is set to 0 when node k and node l are not neighboring.

Next, by substituting (3) into the fact $\theta_{kl} = \theta_{lk} + \pi$, which is obtained by using the alternate interior angles theorem, the equation expressed in absolute angle and orientation is obtained as

$$\alpha_k - \alpha_l = \phi_{lk} - \phi_{kl} + \pi. \quad (5)$$

Let $\boldsymbol{a}(\boldsymbol{\alpha}) = \{e^{i(\alpha_m)}\}^\intercal$ be the set of exponentiation of orientations. By using the modulo 2π angular format, the fundamental relation matrix $\mathbf{B} = \boldsymbol{a}(\boldsymbol{\alpha})\boldsymbol{a}(\boldsymbol{\alpha})^*$ is calculated as

$$\mathbf{B} = e^{i\Psi} + 2\mathbf{I}, \quad (6)$$

where $\Psi = \Phi^\intercal - \Phi + \pi \mathbf{1}_N \mathbf{1}_N^\intercal$, $\mathbf{1}_N$ is a column vector with all components of 1, $\mathbf{I}$ is an identity matrix, and $e^{i\Psi}$ means element-wise exponentiation of Ψ.

Then, in order to complete the matrix $\mathbf{B}$, some elements of $\mathbf{B}$ that correspond to the nodes which are not directly connected have yet to be computed. The element B_{kl}, the element in the k-th row and the l-th column of the matrix $\mathbf{B}$, is obtained as

$$\begin{aligned} B_{kl} &= e^{i(\alpha_k - \alpha_l)} \\ &= e^{i((\alpha_k - \alpha_{h(1)}) + (\alpha_{h(1)} - \alpha_{h(2)}) + \cdots (\alpha_{h(L)} - \alpha_l))}, \end{aligned} \quad (7)$$

where L is the number of intermediate nodes between nodes k and l, and $h(1), \cdots, h(L)$ are the indices for the intermediate nodes between nodes k and l which are determined by the shortest path algorithm (e.g., Dijkstra algorithm). (7) is converted using the fact $\alpha_k - \alpha_l = \phi_{lk} - \phi_{kl} + \pi$ to

$$B_{kl} = e^{i((\phi_{h(1)k} - \phi_{kh(1)} + \pi) + (\phi_{h(2)h(1)} - \phi_{h(1)h(2)} + \pi) + \cdots + (\phi_{lh(L)} - \phi_{h(L)l} + \pi))}. \quad (8)$$

Finally, the set of exponentiation of estimated orientations $\boldsymbol{a}(\hat{\boldsymbol{\alpha}})$ is calculated by using the eigen-decomposition of matrix $\mathbf{B}$. The eigenvector corresponding to the largest eigenvalue of matrix $\mathbf{B}$ is $\boldsymbol{a}(\hat{\boldsymbol{\alpha}})$. The eigen-decomposition is expressed as

$$\mathbf{B} = \mathbf{Q_B} \Lambda \mathbf{Q_B}^\intercal, \quad (9)$$

where $\mathbf{Q_B}$ is a matrix with eigenvectors as column vectors of $\mathbf{B}$ and Λ is a diagonal matrix with eigenvalues as diagonal elements. By using phase angle, the set of estimated orientations $\hat{\boldsymbol{\alpha}}$ is calculated as

$$\hat{\boldsymbol{\alpha}} = \angle \boldsymbol{a}(\hat{\boldsymbol{\alpha}}), \quad (10)$$

where $\angle \boldsymbol{a}(\hat{\boldsymbol{\alpha}})$ is element-wise phase calculation of $\boldsymbol{a}(\hat{\boldsymbol{\alpha}})$. Each local coordinate system of a node is rotated onto the global coordinate system by the corresponding element of $\hat{\boldsymbol{\alpha}}$.

3) ESTIMATING ABSOLUTE ANGLE INFORMATION

Once the coordinate transformation is done, the relative angle of each node is represented on the global coordinate system. The estimated absolute arrival angles $\hat{\theta}_{kl}$ between neighboring nodes k and l on the global coordinate system are obtained by adding the corresponding estimated orientation $\hat{\alpha}_k$ to relative arrival angle ϕ_{kl} as

$$\hat{\theta}_{kl} = \phi_{kl} + \hat{\alpha}_k. \quad (11)$$

Note that, for N nodes, the above process is done by a matrix calculation as

$$\hat{\Theta} = \Phi + \hat{\boldsymbol{\alpha}} \mathbf{1}_N^\intercal, \quad (12)$$

where the set of relative angles Φ on local coordinate systems is in (4), the set of estimated absolute arrival angles $\hat{\Theta}$ is defined as

$$\hat{\Theta} = \{\hat{\theta}_m\} = \begin{bmatrix} 0 & \hat{\theta}_{21} & \hat{\theta}_{31} & \cdots & \hat{\theta}_{N1} \\ \hat{\theta}_{12} & 0 & \hat{\theta}_{32} & \cdots & \hat{\theta}_{N2} \\ \vdots & \vdots & & \ddots & \\ \hat{\theta}_{1N} & & \cdots & \hat{\theta}_{1N-1} & 0 \end{bmatrix}, \quad (13)$$

and $\hat{\boldsymbol{\alpha}} = \{\hat{\alpha}_1, \cdots, \hat{\alpha}_N\}$ is the set of estimated orientations.

B. VECTOR COMBINATION

This section deals with the construction of vectors between nodes that are one or more hops away from each other. After estimating distance and angle values between neighboring nodes, the distance and angle values at each node need to be gathered in one place (e.g., central server or main node) to calculate all the inter-node distances and absolute angle values between nodes that are not directly connected. For the common range-based localization system, the distance value between nodes that are not directly connected is determined by the shortest path algorithm (e.g., Dijkstra or Floyd). But, these distance values are calculated by utilizing vector combination techniques in the proposed method.

In the conventional range-based positioning algorithms with no angle information, the distance between two nodes over more than one hop is commonly calculated by the

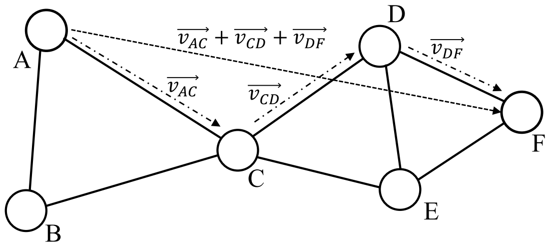

FIGURE 3. Example of the generated vector from node A to node F (three hops).

shortest path algorithm, such as Dijkstra or Floyd. Fig. 3 shows a network with six nodes where, for instance, nodes A and F are located far away enough to take three hops to reach. The distance between nodes A and F is estimated as a sum of the distances over the intermediate nodes $\hat{d}_{AF} = d_{AC} + d_{CD} + d_{DF}$, where d_{AC} is the distance between the nodes A and C, by the shortest path algorithm. Although this estimated distance is different from the actual distance, it is commonly used as an effective distance value between the two nodes over more than one hop.

If the absolute angle information between neighboring nodes is calculated, the distance value closer to the actual distance can be obtained by a combination of vectors. That is, more accurate distance values between two nodes can be derived. In Fig. 3, the vector from node A to node C is computed as

$$\vec{v}_{AC} = d_{AC}\underline{/\hat{\theta}_{AC}}, \tag{14}$$

where d_{AC} is the distance between nodes A and C and $\hat{\theta}_{AC}$ is the absolute angle between nodes A and C given in (11). Similarly, the vector from node C to node D and the vector from node D to node F are computed as $\vec{v}_{CD}$ and $\vec{v}_{DF}$, respectively. Then, the vector from node A to node F is finally calculated by a combination of the vectors as

$$\vec{v}_{AF} = \hat{d}_{AF}\underline{/\hat{\theta}_{AC}} = \vec{v}_{AC} + \vec{v}_{CD} + \vec{v}_{DF}. \tag{15}$$

In order to minimize the effect of multiplicative noise, the vector from one node to another is obtained by combining the vectors along the intermediate nodes of the routing path selected by the shortest path algorithm. As shown above, the vector from node A to node F is computed by the combination of the vectors along the shortest path, having the nodes C and D as intermediate nodes, since it is least affected by multiplicative noise.

As a result of the above vector combinations, $M = N(N-1)/2$ different vectors are obtained. The set of estimated vectors $\hat{\mathbf{V}}$ containing vector information between all pairs of nodes can be represented as

$$\hat{\mathbf{V}} = [\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \ldots, \hat{\mathbf{v}}_M]^\mathsf{T}, \tag{16}$$

where the estimated vector $\hat{\mathbf{v}}_k = [\rho_k cos\hat{\theta}_k, \rho_k sin\hat{\theta}_k]^\mathsf{T}$ is the k-th estimated vector and M is the total number of node pairs.

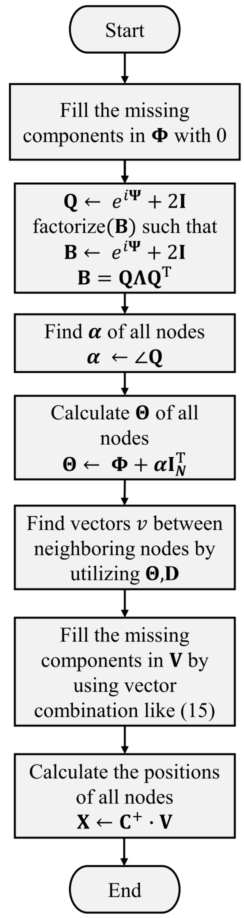

FIGURE 4. Flow diagram of the proposed algorithm.

C. POSITION CALCULATION

This section deals with finding the location of nodes. The set of absolute positions $\hat{\mathbf{X}}$ is obtained as [1, eq. (19)]

$$\hat{\mathbf{X}} = \mathbf{C}^+ \cdot \hat{\mathbf{V}}, \tag{17}$$

where $\mathbf{C}^+$ is the pseudo-inverse matrix of the coefficient matrix $\mathbf{C}$ which is defined as

$$\mathbf{C} = \left[\begin{array}{c|c|c} \mathbf{1}_{N-1\times 1} & \multicolumn{2}{c}{-\mathbf{I}_{N-1\times -1}} \\ \hline \mathbf{0}_{N-2\times 1} & \mathbf{1}_{N-2\times 1} & -\mathbf{I}_{N-1\times N-1} \\ \hline \ddots & \ddots & \ddots \\ \hline \multicolumn{2}{c|}{\mathbf{0}_{1\times N-2} \quad 1} & -1 \end{array}\right]. \tag{18}$$

The set of absolute positions $\hat{\mathbf{X}}$ is expressed as

$$\hat{\mathbf{X}} = [\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \ldots, \hat{\mathbf{x}}_N]^\mathsf{T}, \tag{19}$$

where a absolute position value $\hat{\mathbf{x}}_k = [\hat{x}_{k,1} \;\; \hat{x}_{k,2}]^\mathsf{T}$ is the estimated position of k-th node and $\hat{x}_{k,1}$ and $\hat{x}_{k,2}$ are the first and second coordinate of two-dimensional space. The overall process of the proposed algorithm is indicated in Fig. 4.

IV. PERFORMANCE EVALUATION

Extensive simulations are performed to evaluate the localization performance of the proposed algorithm. Among many localization algorithms in the literature, three existing range-based algorithms (CMDS, MDS-MAP(C,R) [6],

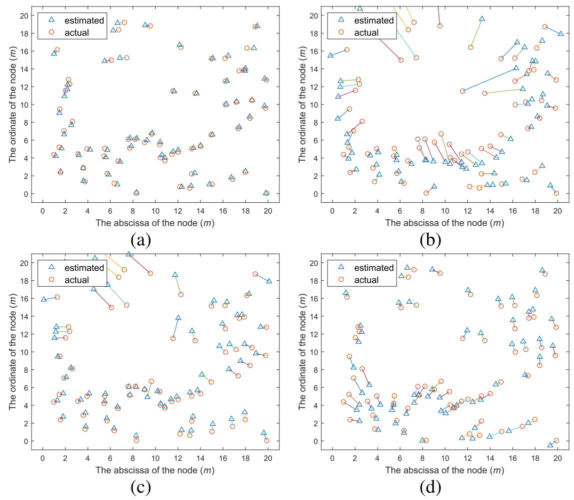

FIGURE 5. Node localization in an environment where nodes are randomly distributed($nf = 0.05$, $\sigma_\phi = 5°$): (a) EHLS(proposed algorithms), (b) CMDS, (c) MDS-MAP(C,R) with 20 refinement iterations [6], and (d) RAST [19].

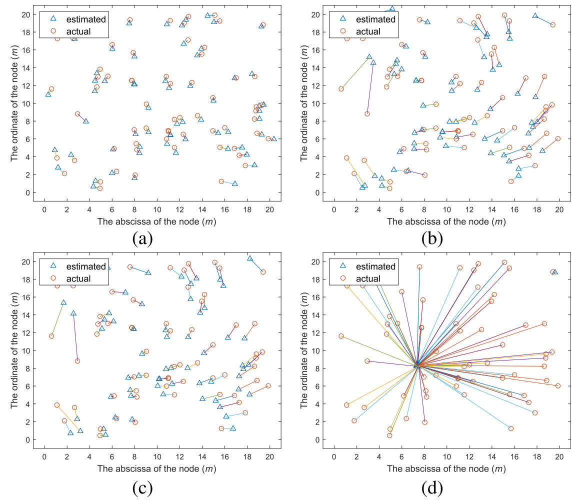

FIGURE 6. Node localization in an environment where nodes are randomly distributed with 1-edge connectivity($nf = 0.05$, $\sigma_\phi = 5°$): (a) EHLS(proposed algorithms), (b) CMDS, (c) MDS-MAP(C,R) with 20 refinement iterations [6], and (d) RAST [19].

RAST [19]) can operate in a large network even when there are nodes that are not directly connected, so these algorithms are suitable for a fair comparison with the proposed algorithm.

In simulations, 64 nodes(N) were randomly distributed in a square area with $20m \times 20\ m$. The communication range for all the nodes is set to $5m$. The positioning errors for each algorithm are obtained by an average of as many as 5000 simulations. MDS-MAP(C,R) was tested by setting the number of repetitions of the refinement process to 1 or 20. The measured distance value is modeled through the change of the distance noise factor nf in (2). For accurate performance evaluation, we evaluate the positioning accuracy of the proposed algorithm from various perspectives (i.e., distance and angle error, node density, the number of routing nodes). In addition, the measured angle value is modeled through the change of the standard deviation of angle error σ_ϕ as

$$\tilde{\phi}_{kl} = \phi_{kl} + N(0, \sigma_\phi^2), \tag{20}$$

where $\tilde{\phi}_{kl}$ and ϕ_{kl} refer to the measured AOA value and the real AOA value, respectively.

A. VISUALIZATION OF THE NODE DISTRIBUTIONS

Fig. 5 visualizes the node distributions, in which 64 nodes are randomly distributed when distance noise factor nf is 0.05 (average error for distance at $5m$ is $0.2m$) and standard deviation of angle error is $\sigma_\phi = 5°$ (average error for angle is 4°). The actual node locations and the estimated locations by each algorithm are plotted for comparison purposes. As shown in the figures, the proposed algorithm provides higher positioning accuracy than the conventional algorithms in a random node distribution with small angular error. Note that RAST calculates the position of the node with only angle information and shows relatively good positioning results in an environment with little error in angle measurements.

Fig. 6 shows the node distributions with randomly distributed nodes with 1-edge connectivity when distance noise factor is $nf = 0.05$ and the standard deviation of angle error is $\sigma_\phi = 5°$. As illustrated in the figures, the conventional range-based algorithms show poor positioning performance in a network with 1-edge connectivity. In particular, as shown in Fig. 6, the positioning error of RAST is very high because of the node with the 1-edge connectivity at the bottom left of the network. Since RAST requires each node to have connections with at least two neighboring nodes to compute the distance, it fails to predict the size of the whole network with 1-edge connectivity and thus it is confirmed that huge positioning errors occur. On the other hand, the proposed algorithm is more robust and provides higher positioning accuracy than the conventional algorithms even in a network with 1-edge connectivity.

B. DISTANCE AND ANGLE ERROR

Measurement error is a very important parameter in a wireless sensor network. Fig. 7 shows the positioning error of the algorithms as a function of distance noise factor nf in a random node distributed environment with a certain angle error. Since the positioning error of RAST is often very high in networks with 1-edge connectivity, RAST is excluded in the figure to make a fair performance comparison with the proposed algorithm. Fig. 7(a) shows a comparison of positioning errors when the reliability of measured AOA was high ($\sigma_\phi = 5°$). In all cases, the proposed algorithm has more than 50% higher positioning performance than the conventional algorithms. In particular, in an environment where distance noise factor nf is less than 0.05, the proposed algorithm has about 62% improvement of positioning error performance in compared to MDS-MAP(C,R) with 20 refinement iterations. Fig. 7(b) shows a comparison of positioning errors when the standard deviation of angle error σ_ϕ is 13° (average error for angle is 10.4°). It is clear that the proposed algorithm shows higher

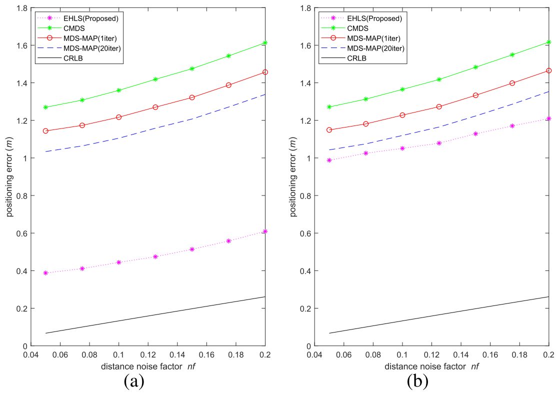

FIGURE 7. The effect of the distance measurement error on positioning accuracy when there is angle measurement error: (a) $\sigma_\phi = 5°$ and (b) $\sigma_\phi = 13°$ ($N = 64$).

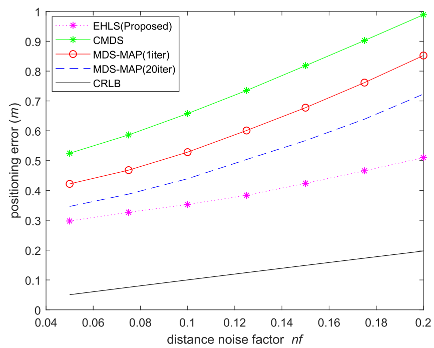

FIGURE 8. The effect of the distance measurement error on positioning accuracy when there is angle measurement error ($N = 100$, $\sigma_\phi = 5°$).

positioning performance than the conventional algorithms in all cases. In particular, the proposed algorithm has 10% higher positioning performance improvement compared to MDS-MAP(C,R) with 20 refinement iterations even in the environment where distance noise factor nf is low ($nf = 0.2$: average error for distance at $5m$ is $0.8m$).

Fig. 8 shows the positioning error of the algorithms as a function of distance noise factor nf in a random node distributed environment when set to a different node density ($N = 100$, $\sigma_\phi = 5°$). The proposed algorithm shows higher positioning performance than the conventional algorithms in this environment. Through the above simulations, it is confirmed that the proposed algorithm has higher positioning performance than the conventional algorithms in an environment with small angular errors. Also, it is worth noting that the positioning performance of the proposed algorithm increases as the angle error becomes smaller with a given distance noise factor nf.

C. NODE DENSITY

In order to more accurately evaluate the effect of node density, the positioning accuracy was calculated using node density as a variable. The distance noise factor nf was fixed at 0.1 and the standard deviation of angle error σ_ϕ^2 was fixed at 5° in these simulations. Fig. 9 shows the positioning error of the algorithms while changing the density of the nodes. It is confirmed that as the density of nodes increases, the difference in positioning accuracy between the proposed

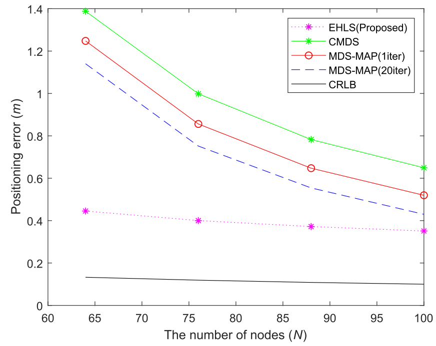

FIGURE 9. The effect of node density on positioning accuracy ($nf = 0.1$, $\sigma_\phi = 5°$).

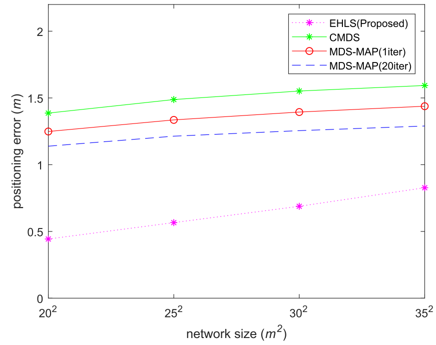

FIGURE 10. The effect of the number of routing nodes on positioning accuracy ($nf = 0.1$, $\sigma_\phi = 5°$).

algorithm and the existing algorithm is reduced. This can be interpreted as the result that the increase in node density reduces the 1-edge connectivity situation, resulting in few unpredictable situations in the conventional distance-based algorithms. In other words, the proposed algorithm is robust with a high positioning performance even in the network with 1-edge connectivity.

D. NUMBER OF ROUTING NODES

To evaluate the effect of this parameter, we calculated the positioning accuracy as the size of the node distribution area changes while maintaining the node density. Fig. 10 shows the positioning error of the algorithms while changing the number of routing nodes. In order to maintain the node density, when the sizes of the node distribution area are $20m \times 20m$, $25m \times 25m$, $30m \times 30m$, and $35m \times 35m$, the number of nodes (N) is set to 64, 100, 144, and 196, respectively. The distance noise factor nf was fixed at 0.1 and the standard deviation of angle error σ_ϕ^2 was fixed at 5° in these simulations. Even if the network size increases in an environment with small angular errors, the proposed algorithm shows higher positioning performance compared to other algorithms.

V. CONCLUSION

A novel hybrid localization algorithm is proposed in this paper. For large networks with some nodes that are not directly communicated, the positions of all the nodes in the network are estimated using distance and angle information. The proposed algorithm can compute the vector between two nodes with multi-hops by utilizing the vector combination.

Even though the proposed method is a noniterative form that is calculated at once, better results can be obtained when compared with the iterative method in a random node distribution environment with small errors in AOA. In particular, in an environment where distance noise factor *nf* is low ($\sigma_\phi = 2.25°$), the proposed algorithm improves the positioning performance up to 70% as compared to the conventional iterative method such as MDS-MAP(C,R) with 20 refinement iterations. In addition, the proposed algorithm is shown to be robust such that little positioning performance degradation is observed even in a network with 1-edge connectivity.

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