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A Node Self-Localization Algorithm With a Mobile Anchor Node in Underwater Acoustic Sensor Networks

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ABSTRACT Aiming at improving the localization accuracy, reducing network cost, and energy loss in the 3-D environment, this paper proposes a mobile node localization algorithm based on compressive sensing for underwater acoustic sensor networks (UASNs). By dividing the cubic module of the underwater monitoring area and using the energy between the mobile anchor node and the unknown nodes, the sparse localization problem based on the cubic module is transformed into the nodes localization problem based on compressive sensing. Since the energy localization between nodes based on cubic modularization is adopted, the path of the mobile node does not need to be specially designed, as long as the mobile beacon node traverses the entire cubic module. Considering the distance problem of the moving path, the mobile node path is based on the random waypoint (RWP) and the LAYERED-SCAN model. The simulation results show that the proposed algorithm can be applied to the node localization problem of UASNs. It can reduce network cost and node energy loss while obtaining higher localization accuracy.

INDEX TERMS Underwater acoustic sensor networks, node localization, compressive sensing, mobile anchor node.

I. INTRODUCTION

With the increasing demand for abundant marine resources and the continuous development of ocean detection technology, in the underwater communication scenarios, it is important to improve system capacity and spectral efficiency [1], [2]. Underwater Acoustic Sensor Networks (UASNs) plays an irreplaceable role in the field of ocean exploration technology [3], [4]. UASNs have been widely used in marine data collection, pollution monitoring, offshore exploration, disaster prevention, auxiliary navigation, tactical surveillance, etc., and have attracted more and more research interest in recent years [5], [6]. However, due to the particularity of the underwater channel, the UASNs has the following characteristics compared with the traditional wireless sensor network [7]–[9]: 1) high transmission delay and limited available bandwidth. Since the propagation rate of acoustic wave under water is 5 orders of magnitude lower than that of radio waves in the air, it has a communication delay of 0.67 s/Km and varies with the temperature, salt and pressure of the water; 2) broadcast loss is large and multipath is serious. The acoustic wave has a large attenuation of signal transmission energy due to the existence of propagation loss, absorption loss, scattering loss and reflection loss in the underwater channel. Due to the refraction of the layered medium in the water area and the reflection of the water surface and the bottom, there are many different paths between the acoustic sources and the nodes, so that the amplitude and phase of the received acoustic signal will be distorted; 3) limited node energy. Security is a challenging issue for UASNs to be used [10], and spectrum sensing and channel optimization issues cannot be ignored [11]–[13]. Due to the lack of convenient and renewable resources underwater, the operation of the UASNs relies mainly on the limited load of battery work on the nodes. And the underwater environment is complicated, the sensors in the waters cannot replenish energy by replacing the batteries, so the energy consumption of the underwater nodes must be required to be lower. In addition, due to the floating of water flow, how to make the deployment of nodes stable is also an important issue in the deployment of UASNs. Therefore, how

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to accurately locate the underwater unknown nodes position with low network cost and energy consumption is a hot issue in UASNs localization research, and it is also a basis for its application.

Mobile node localization as a drone surveillance has become a very important but largely underexplored topic [14], [15]. Existing 3-D environment mobile node localization mainly has two research directions, node self-localization algorithm and mobile node path selection [16]. The typical node self-localization algorithm can be divided into range-based localization algorithms and range-free localization algorithms. The range-based localization algorithm requires the sensor nodes to measure signal strength indicator (RSSI) [17], time of arrival (TOA), time difference of arrivals (TDOA) and angle of arrival (AOA) [18], [19]. And then combined with trilateral, trigonometry, least squares methods, etc. The range-free algorithm mainly relies on the connected information of the nodes to complete the localization, such as DV-hop, convex optimization algorithm, centroid algorithm, etc. In general, the range-free algorithm is lower in cost than the range-based algorithm, but the localization accuracy is also lower. This paper prioritizes the energy-based range algorithm. At this stage, the path planning of mobile nodes in 3-D environment is also a research hotspot. The researchers are committed to how mobile nodes can traverse the entire monitoring area with the shortest path in the shortest time and obtain high localization accuracy. Literature [16] gives an overview of mobile node path planning, including single mobile node localization, multiple mobile nodes localization, and some paths design issues. Although there are more path planning, the starting point of these path planning is based on the trilateration algorithm, and to obtain better localization accuracy, complex moving paths are needed, which is a big test for localization time and node energy consumption. And because of the large delay under water, the range-based algorithm cannot be well applied. The problem of signal processing is becoming more and more interesting [20]–[22]. In the sensor networks, how to solve the problem of insufficient information processing capability of nodes is also the key to locate.

Compressive sensing(CS) [23], [24] theory as a new sampling theorem can be sampled far below the Nyquist sampling theorem. Applying the compressive sensing to the node localization algorithm can solve the problem of insufficient information processing capability of the node. By acquiring the information of a small number of nodes of the network, the entire network can be known, the network cost is reduced, and the energy consumption is saved.

In summary, this paper proposes a mobile node localization algorithm based on compressive sensing, which is applied to the node localization of UASNs. The localization of the energy information between the nodes effectively solves the problem of ranging error caused by the transmission delay in the underwater. In addition, for higher localization accuracy, trilateration requires complex planning of the mobile node path. The algorithm of this paper is based on the sparse cube lattice localization algorithm, without considering the collinear problem of the mobile node, as long as the mobile node traverses the entire square. Therefore, the LAYERED-SCAN path can achieve higher localization performance, save localization time and energy consumption. According to the literature [25]–[27], an Orth-based sparse target localization algorithm is proposed. The observation dictionary cannot satisfy the RIP property, and QR-decomposition is performed on the sensing matrix. The new observation dictionary satisfies the RIP property and does not affect the sparsity of the original sparse signal in the QR-decomposition preprocessing process, thus ensuring the reconstruction performance of the algorithm and improving the localization accuracy of the node. In this paper, the Orth algorithm and QR-decomposition algorithm are studied. When the mobile node follows the RWP path and the LAYERED-SCAN path, the localization error varies with the number of times the mobile node sends information, the SNR and the number of unknown nodes. The simulation results show that the proposed QR-decomposition algorithm has higher localization accuracy and robustness when the mobile beacon node follows the LAYERED-SCAN path.

The rest of this paper is organized as follows. The second section explains the related work of this paper. The third section introduces the network localization model and algorithm. The fourth section analyzes the simulation results. The full text is summarized in the fifth section.

II. RELATED WORK

For the underwater acoustic sensor mobile node localization, the mobile beacon node path and localization algorithm is worthy of our two research directions, of course, the network security of UASNs cannot be ignored. How to use simple path planning, lower network cost, and higher localization accuracy has always been the focus of research by scholars. Many existing path plans are applied under specific algorithms. Among them, there are many paths designed for the trilateration method. In order to solve the collinear problem of the trilateral method, it is necessary to design a complicated path, which brings time to the localization and Energy consumption. How to find an algorithm that is suitable for simple paths and obtain better localization accuracy is also a problem worth considering. In addition, the application of the compressive sensing algorithm in sensor network localization has been a topic of great interest in recent years. Compressive sensing can greatly reduce the network cost and avoid the problem of insufficient information processing capability of nodes.

Han *et al.* [28] addressed the problems of energy constraints and characteristics of water delamination of autonomous underwater vehicles (AUVs) in UASNs, proposing a stratification-based data collection scheme. By stratifying the network, the power consumption of data collection is reduced, and the network lifetime is improved.

Jiang *et al.* [29], [30] proposed a novel trust model based on cloud theory (TMC) for UASNs. The algorithm effectively solves the uncertainty and ambiguity of traditional cloud theory and improves network security. Han *et al.* [31] proposed an attack-resistant trust model based on multidimensional trust metrics (ARTMM). This method realizes accurate and efficient trust evaluation for UASNs system, compared with the traditional method, the accuracy of evaluation is improved and the energy consumption is reduced.

Yan *et al.* [32] studied the relationship between propagation delay and node position in UASNs, and proposed an asynchronous localization algorithm with mobility prediction. It is used to estimate the future position of the active and passive sensor nodes, which reduces the ranging errors caused by the delay to some extent. Compared with the synchronous localization algorithm, the algorithm improves the localization accuracy and time.

Lee and Kim [33] applied a mobile beacon-based range-free localization method to UASNs, which periodically broadcasts beacon messages containing its location. Ordinary nodes receive a set of potential candidate values by receiving this information, and use a weighted centroid algorithm to locate unknown nodes.

Alomari [34] made a new plan for the path of the anchor node's movement, called the H curve. It has higher coverage and localization accuracy than some traditional paths. However, the path is proposed for the trilateration localization algorithm. In the UASNs, the range-based method is not well applicable due to the different acoustic propagation speeds and the transmission delay. In addition, complex paths also burden the movement of anchor nodes. In order to achieve high network connectivity and coverage, and improve localization accuracy, Han *et al.* [35] studied node deployment in UASNs. The simulation results show that the positive tetrahedral deployment scheme is better than random deployment and cube deployment in reducing localization error and improving localization rate when using trilateration method localization, while maintaining the average number of adjacent anchor nodes and reasonable network connectivity. Therefore, in addition to the localization accuracy, whether the localization of unknown nodes in the whole network can be realized is also an issue that our algorithm should consider. From the perspective of achieving the best localization performance with the simplest path and considering the underwater environment, we hope to locate the unknown nodes by moving the energy of the anchor node and the unknown nodes.

In the literature [36], Zhao *et al.* proposed a sparse target localization algorithm based on LU-decomposition. Based on the Orth algorithm, the algorithm decomposes the sensing matrix, which satisfies the compressive sensing RIP property without changing the sparseness of the original signal, and obtains good localization performance. Although the algorithm is proposed for 2-D environment and static beacon nodes, it brings great inspiration to our work.

Although underwater localization technology has always been the focus of people's research, many existing algorithms are developed for static node positioning, and in order to achieve better localization performance, complex planning of paths in 3-D environment is required. This paper combines compressive sensing to improve the orth sparse target localization algorithm and propose a QR-decomposition algorithm. By dividing the monitoring area into cubes, according to the energy relationship between the anchor node and the unknown node, combined with the centroid algorithm to locate unknown nodes. This algorithm does not require complex design of the mobile node path, nor does it need to consider the collinear problem. The basic SCAN path can be well applied and can locate all unknown nodes. After simulation, the location error of the two algorithms under RWP and layered scan path is compared with the times of the anchor node sends information, the SNR and the unknown nodes number change. The results show that the QR-decomposition algorithm has smaller localization errors under the LAYERED-SCAN path conditions. The specific localization model and algorithm will be elaborated in the following.

III. SYSTEM MODELS AND ALGORITHMS

Suppose that in a 3-D environment underwater sensing area, we first divide it into modules and divide it into N small cube modules. Then we use the winch device proposed in [35] to deploy K unknown locations. The sensor can control its own height by air pump, which can avoid unknown nodes floating with water flow. Through the energy relationship between the mobile anchor node and the unknown nodes, the localization problem of the unknown nodes is transformed into a square-based localization problem. The anchor beacon node first needs to send M pieces of information in the sensing area, and the signals of each unknown node are received, and then respectively send the signal strength values of the respective unknown nodes received to the fusion center. Finally, the fusion center uses the target algorithm based on compressive sensing to locate the nodes, determine the specific position of the unknown nodes in the grids, and then combine the centroid algorithm to further reduce the localization error. In addition, since the localization algorithm adopts the compressive sensing algorithm and locates the energy between nodes, the mobile anchor node can locate all unknown nodes by receiving a small amount of information, so the path of the mobile node selects the basic RWP model and LAYERED-SCAN model.

The actual underwater environment is more complicated than the ideal environment. The theoretical model is relatively complicated due to the absorption of the water medium itself, the expansion of the acoustic wave front and various uneven scattering in the water. According to the law of acoustic wave propagation under water, the main influence of energy attenuation of target signal in the process of underwater acoustic channel transmission comes from the following four aspects [37]: 1) geometric extension of the wavefront; 2) Loss of acoustic waves on the surface of the water and the bottom of the water; 3) absorb; 4) scattering. The first two of them cause an exponential decay of the acoustic intensity, which

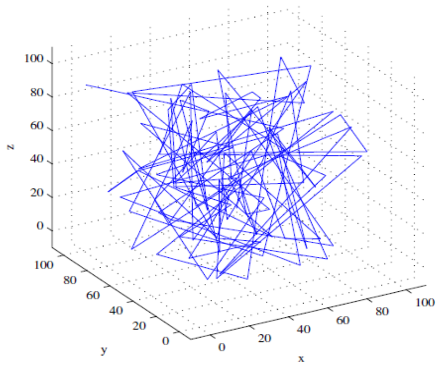

FIGURE 1. RWP model.

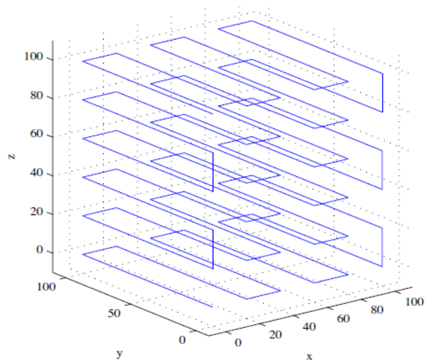

FIGURE 2. LAYERED-SCAN model.

is the attenuation loss. According to the empirical formula of underwater acoustic propagation, in a homogeneous medium, the change of the intensity of the target radiation signal is expressed by the TL (Transmission Loss), which quantitatively describes the attenuation relationship of the acoustic intensity as a function of distance:

$$TL(d,f) = n \times 10\lg d + \alpha_f \cdot d \times 10^{-3} \tag{1}$$

The first term of equation (1) represents the spread loss of underwater acoustic signals in water, the second term is the absorption loss (caused by absorption and scattering factors), and n is the mode of acoustic wave propagation. d is the Euclidean distance between the target and the node. The acoustic absorption coefficient α_f satisfies the following empirical formula, where f is expressed in kHz.

$$\alpha_f = \frac{0.102f^2}{1+f^2} + \frac{40.7f^2}{4100+f^2} + 2.75 \times 10^{-4}f^2 \tag{2}$$

Although the underwater environment is more complicated, the attenuation of acoustic energy is affected by the density, salinity and temperature of the water medium, but in a small water range (when the transmission distance is less than 2km), the attenuation loss term of the target signal during the underwater acoustic channel transmission is the determinant of the signal energy loss. The absorption and scattering factors have very little influence on the acoustic energy attenuation, which can be ignored. That is, in the propagation loss $TL(d,f) = n \times 10\lg d + \alpha_f \cdot d \times 10^{-3}$, the absorption loss term $\alpha_f \cdot d \times 10^{-3}$ can be omitted, there is:

$$TL(d,f) \approx n \times 10\lg d \tag{3}$$

n is the way the target sound wave propagates underwater. For example, when $n = 0$, the acoustic wave propagates in the far-field plane wave, $n = 1$ is the cylindrical wave, and $n = 2$ is the spherical wave. Since this paper is based on the near-distance underwater acoustic signal intensity transmission model, the far-field plane wave condition is not applicable when $n = 0$, and the cylinder wave is assumed to be simulated. Based on this principle, we can give a simplified channel model, given by equation (3):

$$RSS(d) = P_t - 10\lg d \tag{4}$$

where $RSS(d)$ is the received signal strength, which is the distance between the cube where the signal source is located and the cube where the receiver is located, and P_t is the source signal strength. In our model, we made a few assumptions:

1) The monitoring environment is a 3-D static underwater area, and the movement of unknown sensor nodes is within an acceptable range, which can be ignored.

2) The nodes are independent of each other, and all unknown nodes are in the area to be monitored.

3) There is only one sensor node in each small cube, and the sensor nodes have the same communication radius.

IV. INTRODUCTION TO LOCALIZATION ALGORITHM

In the localization model based on compressive sensing, assuming that the sequence number of the cube of the k -th $(1 \le k \le K)$ unknown node is n, the position of K unknown nodes in the cubic lattice can be represented by an matrix $\mu_{N\times K}$ of $N \times K$ as follows:

$$\mu = [\mu_1, \cdots, \mu_k, \cdots, \mu_K] \tag{5}$$

where μ_k is a vector of $N \times 1$ except that elemen $\mu_k\ (n)$

$$Y = \Phi\Psi\mu + \varepsilon \tag{6}$$

where $Y_{M\times K}$ is the observed value, $\Psi_{N\times N}$ is a sparse transform base, which can be obtained by signal transmission attenuation model $\Psi_{i,j} = RSS\left(d_{i,j}\right)$, indicating the received signal strength from the i-th cube to the j-th cube. $\Phi_{N\times M}$ is an observation matrix whose i-th $(1 \le i \le M)$ row element represents the ordinal number of the cubic lattice in which the mobile beacon node i-th sends the message. If it is 1 in the cube, otherwise it is 0, that is, each element of its row has only one element value of 1, the others are all 0, ε is Gaussian white noise.

Since the sparse transformation matrix and the observation matrix in the model are related, the resulting observation dictionary cannot satisfy the RIP properties. In order to solve this problem, Feng et al. [26] proposed a sparse target localization algorithm based on Orth. The algorithm first performs orth-based pre-processing on the signal, and then performs signal reconstruction and target localization. Signal pre-processing is as follows:

$$Y' = TY = T(\Phi\Psi\mu + \varepsilon) \tag{7}$$

where T represents a linear transform operator. Let the observation dictionary $A = \Phi\Psi$ then there is $T = QA^*$, where $(\cdot)^*$ represents the inversion of the matrix, $Q = orth(A^T)^T$. orth $(\cdot)$ represents a matrix column orthogonal transform, and $(\cdot)^T$ represents a matrix transpose operator.

After pre-processing, the new sensing matrix is an orthogonal transformation matrix, which satisfies the RIP property, but affects the sparseness of the newly reconstructed signal, so it affects the performance of the localization result. Therefore, we have done a matrix decomposition on the observation dictionary to improve the positioning performance.

First, QR-decomposition is performed on the observation dictionary a as shown in the following equation:

$$A^T = QR \tag{8}$$

where Q is a standard orthogonal matrix of $N \times N$ and R is an upper triangular matrix of $N \times M$. Therefore, the matrix A can be expressed as:

$$A = R^T Q^T \tag{9}$$

where $R^T = [S_{M\times M} 0_{M\times(N-M)}]$, and S is the lower triangular array. Multiply the left side of A by an inverse matrix S^*, and obtain the matrix U as follows:

$$U = S^* A = S^* R^T Q^T = [I_{M\times M} 0_{M\times(N-M)}]Q^T \tag{10}$$

where $I_{M\times M}$ is a M-order unit matrix, it can be seen from the above formula that the matrix formed by the first M rows of Q^T is the matrix U. Therefore, the row vectors of U are unit vectors and are orthogonal to each other.

Then, the matrix U is unitized, and the new observation dictionary B is determined to be:

$$B = U \begin{bmatrix} 1/\|U_1\| & 0 & \cdots & 0 \\ 0 & 1/\|U_2\| & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1/\|U_N\| \end{bmatrix} \tag{11}$$

Finally, we can obtain a new observation Y':

$$Y' = B \begin{bmatrix} \|U_1\| & 0 & \cdots & 0 \\ 0 & \|U_2\| & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \|U_N\| \end{bmatrix} \mu = B\mu' \tag{12}$$

It can be seen from the above formula: μ' is obtained by multiplying the left side of μ by a diagonal matrix. Since μ is sparse, μ' is also sparse, and μ' is the same as μ sparseness. And because the matrix B fully satisfies the RIP properties, therefore, according to the theory of compressive sensing, μ' can be accurately reconstructed. Further, the original signal μ can be obtained by the following formula:

$$\mu = \begin{bmatrix} 1/\|U_1\| & 0 & \cdots & 0 \\ 0 & 1/\|U_2\| & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1/\|U_N\| \end{bmatrix} \mu' \tag{13}$$

Since the actual unknown nodes are randomly distributed, that is, the unknown nodes are not necessarily at the center of the grid, the original signal reconstructed by CS is only an approximate sparse signal. In order to reduce the localization error, this paper uses a weighted centroid algorithm to estimate the position of the nodes.

First, the position vector μ_k of the k-th unknown node is normalized to obtain the weight $\omega_k(n)$ of the n-th cube unit for estimating the coordinates of the k-th unknown node.

$$\omega_k(n) = \mu_k(n) / \sum_{n=1}^{N} \mu_k(n) \tag{14}$$

Then, the weighted centroid algorithm [38], [39] is used to estimate the position of the k-th unknown node:

$$(x_k, y_k) = \sum_{n=1}^{N} \omega_k(n)(x_n, y_n) \tag{15}$$

where (x_k, y_k) represents the estimated position of the k-th unknown node and (x_n, y_n) represents the coordinates of the center of the n-th cube.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. SELECTION OF ANCHOR NUMBER

In the entire monitoring area, as the anchor node moves, the number of anchor points perceived by unknown nodes continues to increase. It is known in [40]: when M is greater than or equal to $O(C \cdot k \cdot \mu^2 \cdot (\log N)^4)$, the algorithm can accurately reconstruct the original signal, where k is the sparsity of the signal and C is a constant, $\mu = \sqrt{N} \max_{i,j} |\Phi_{i,j}|$. In other words, the unknown nodes does not need to perceive all anchor nodes for localization. In order to select the appropriate number of anchor points, this paper first abstracts the monitoring area as a single unknown node location problem. The sensing area to be monitored is set to a cubic area of 100m $\times$ 100 m$\times$ 100m, which is divided into 1000 cubic cells of 10m $\times$ 10m $\times$ 10m. M sensors are randomly distributed, and the energy transmitted by the node is -40dB. We increase the number of sensors and get a rough curve of the localization error as a function of the number of sensors.

As can be seen from the figure 3, with the number of sensors increases, the localization errors of both algorithms are decreasing. When the number of sensors reaches 25, the localization error no longer changes significantly, which reflects to some extent the minimum number of sensors needed to locate an unknown node, that is, the number of times the mobile anchor node information is received. Therefore, in practice, for the sake of insurance, any unknown

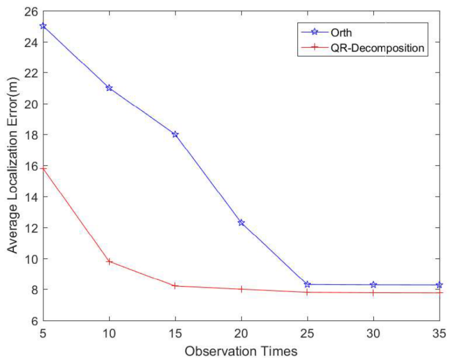

FIGURE 3. The relationship between localization performance and the number of sensors.

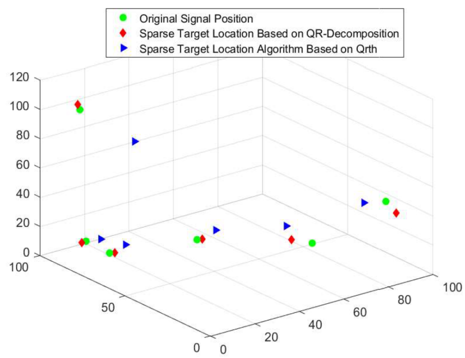

FIGURE 4. Node localization diagram.

node can select its energy relationship with the 30 beacon nodes with the largest energy to locate it, which ensures the localization accuracy under the premise of reducing energy consumption and localization time.

B. NODE LOCALIZATION

Figure 4 is a schematic diagram showing node localization of the two algorithms under the condition that the unknown node K is 6, the mobile anchor node selects the RWP model, and the unknown node senses the anchor node number M is 30. The green dot indicates the original signal, the red diamond indicates the signal position obtained based on the QR-decomposition algorithm, and the blue triangle indicates the signal position obtained based on the orth algorithm. From the figure we can find that the localization algorithm based on QR-decomposition is obviously better than the orth localization algorithm. This is because the sparse target localization algorithm based on orth pre-processing guarantees that the observation dictionary satisfies the RIP property, but the sparsity of the signal is affected in the orth pre-processing process. The sparse target localization algorithm based on QR-decomposition guarantees that the observation dictionary satisfies the RIP property without affecting the sparsity of the signal. Therefore, the localization performance of the sparse target location algorithm based on QR-decomposition is superior to the sparse target localization algorithm based on orth pre-processing.

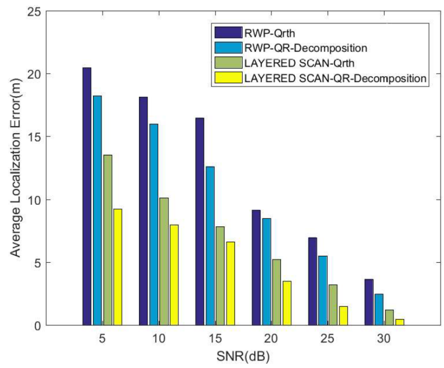

FIGURE 5. Relationship between localization performance and SNR.

C. INFLUENCE OF NOISE ON LOCALIZATION PERFORMANCE

In the 100m $\times$ 100m $\times$ 100m cube monitoring area, it is divided into 1000 small cubic cells of 10m $\times$ 10m $\times$ 10m, and 40 unknown sensor nodes are randomly distributed. The moving path of the anchor node are LAYERED-SCAN and RWP. The moving speed is 10m/s, the anchor node is broadcasted once every 1 second, and the broadcast signal is broadcasted 1000 times. When the anchor node sensed by the unknown node exceeds 30 times, 30 of the signals with the strongest signal strength are selected for localization. When less than 30 times, the actual number of times is used for localization. Figure 5 shows the variation of localization error with increasing SNR between the two algorithms in two paths. As can be seen from the figure, as the SNR increases, the localization error is decreasing. Under the same path conditions, the QR-based algorithm has better localization performance than the Orth algorithm, and the QR algorithm with layered scan path has the smallest localization error when the SNR is fixed. In addition, we can also find that for the same algorithm, the localization performance of the LAYERED-SCAN path is much better than the RWP path. This is mainly because the anchor node can traverse to the center of each small cube along the LAYERED-SCAN path, which fits perfectly with our algorithm model, assuming that the anchor node are distributed in the unit cube. When the RWP path is adopted, the anchor node is not necessarily at the center of the unit cell, and because of the randomness, the information of the anchor node in the monitoring area is unevenly distributed, which may result in the unknown node in some areas not being well positioned.

D. INFLUENCE OF THE NUMBER OF UNKNOWN NODES ON THE LOCALIZATION PERFORMANCE

Figure 6 is a localization performance diagram of different algorithms and paths as the number of unknown nodes changes when the SNR is 30 dB. We still find that the QR-decomposition algorithm with LAYERED-SCAN path has the smallest localization error when the number of unknown nodes are constant, and the Orth algorithm with RWP path has the worst localization performance.

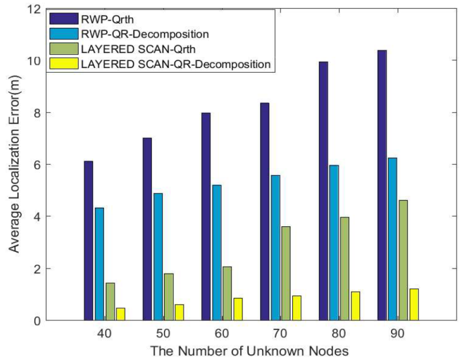

FIGURE 6. Relationship between localization performance and the number of unknown nodes.

In addition, we will find that as the number of unknown nodes increases, the localization error will increase to some extent. This is because the unknown nodes are used as the reconstructed original signal in this paper. In the theory of compressive sensing, the more sparse the signal, the better the reconstruction performance. Therefore, as the number of unknown nodes increases, the sparseness of the equivalent signal decreases, and the localization error increases.

VI. CONCLUSION

In this paper, the UASNs anchor node localization problem is transformed into a dimensionality vector reconstruction problem with a sparsity of 1. For the problem that the observation dictionary does not satisfy the RIP property, a new node localization algorithm based on QR-decomposition is proposed. The algorithm obtains a new observation dictionary through QR-decomposition, which fully satisfies the RIP properties. Different from the Orth-based sparse target localization algorithm, the signal pre-processing of the proposed algorithm does not affect the sparseness of the original signal, thus ensuring the performance of the compressive sensing reconstruction algorithm and improving the performance of the multi-nodes localization algorithm. In addition, this paper applies the algorithm to anchor node localization, introducing RWP path model and LAYERED-SCAN path model. The experimental results show that the node localization algorithm based on QR-decomposition can be well applied to mobile anchor node localization. When the mobile anchor node follows the LAYERED-SCAN path model, it achieves a better localization effect. Compared with the RWP path model, it has better noise immunity, adaptive and lower localization accuracy. Therefore, the algorithm does not require complex planning of the mobile anchor node path. Since the node localization based on the energy between the nodes avoids the influence of the underwater environment on the trilateration localization, and does not need to consider the collinear problem of the mobile anchor node. The LAYERED-SCAN path model can be well applied to the localization model of the algorithm, avoiding the localization time consumption and energy consumption caused by the complicated path. The algorithm reduces network cost while achieving better localization performance, so it is a promising thing to apply the algorithm to UASNs localization. Of course, whether there is a better moving path and the localization performance of the algorithm in an obstacle environment is a subject worthy of our study.

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