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Sensor-Networked Underwater Target Tracking Based on Grubbs Criterion and Improved Particle Filter Algorithm

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ABSTRACT For target tracking in underwater wireless sensor networks (WSNs), the contributions of the measured values of each sensor node are different for data fusion, so a better weighted nodes fusion and participation planning mechanism can obtain better tracking performance. A distributed particle filter based target tracking algorithm with Grubbs criterion and mutual information entropy weighted fusion (GMIEW) is proposed in this paper. The Grubbs criterion is adopted to analyze and verify the information obtained by sensor nodes before the information fusion, and accordingly some interference information or error information can be excluded from the data set. In the process of calculating importance weight in particle filter, dynamic weighting factor is introduced. The mutual information entropy between the measured value of the sensor nodes and the target state is used to reflect the amount of target information provided by sensor nodes, thus a dynamic weighting factor corresponding to each node can be obtained. The simulation results show that the proposed algorithm effectively improves the accuracy of prediction of target tracking system.

INDEX TERMS Underwater wireless sensor networks, target tracking, particle filtering, Grubbs criterion, mutual information entropy.

I. INTRODUCTION

With the rapid development and maturity of the technologies of chip design and embedded systems, sensors are gradually developed towards miniaturization and integration with perceptual computing and networked communication capabilities. In the late 1990s, the US proposed the wireless sensor networks (WSNs). WSN consists of a large number of intelligent sensor nodes with communication and computing capabilities, which are densely deployed in the monitoring area, and can perform specified tasks autonomously according to the environment characteristic. The underwater WSN is an extension of the terrestrial sensor network with more communication technology and information processing challenges [1]–[4]. It has the inherent advantages of self-organization, wide coverage, high fault tolerance, high-precision measurement, low cost of networking, and flexible structure. Therefore, it has been widely used in monitoring marine ecological environment, marine resources detection, and marine search and rescue as well [5].

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Underwater target tracking is of great significance in the study of underwater WSNs. However, duo to the special marine environment, the processing to the interference information, economic deployment and activation of the nodes and tracking accuracy to improve are the main urgent problems to be solved. Some scholars have done a lot of in-depth researches. In [6], particle filter algorithm combined with the interactive model was used to solve the nonlinear and maneuvering target tracking problems in 3D scenes, but the energy consumption problem was not considered. Therefore, the algorithm is not applicable to underwater WSNs. Dehnavi et al. proposed a three-dimensional underwater target tracking algorithm [7], and the extended Kalman filter and Unscented Kalman filter were used to estimate the target path by filtering measurement noise. A local node selection (LNS) scheme was proposed in [8], and the distributed Kalman filter with feedback was used to perform tracking. The authors in [9] proposed an adaptive method based on Kalman filtering to track moving target in a three-dimensional space of underwater WSNs, and about 60% of the closer sensor nodes are activated along the path of the moving target to participate in the tracking task, and the tri-lateration method is used to estimate the position of the target at each stage. Isbitiren and Akan [10] proposed a 3D underwater tracking method in underwater WSN. The distance between the nodes and the target is determined by the arrival time of the target's noise signal, and the tri-lateration is used to calculate the position of the target, thus the target is tracked by repeating the process above. However, this method has no prediction procedures, so that it cannot provide high tracking accuracy. Information theory is also widely used in sensor management problems. Probability-of-detection was computed using both grid cell and particle filter estimators, and experimentally demonstrated in [11]. Authors in [12] used an approximation method to estimate the expected entropy of particle filters over a finite time horizon. Hoffmann and Tomlin [13] studied the selection metric based on mutual information entropy, and selects the sensor by maximizing the mutual information entropy between the measurement of the node and the target state.

However, there are still some problems in the current target tracking that are not well solved by the above methods. Since underwater sensors need to work in extreme underwater environments, there will be redundancy and anomalous data during the measurement process to affect the target tracking accuracy. Sensors for underwater WSN are battery powered and it is not feasible to replace the battery when the battery is exhausted. This means that battery life affects the life of the entire network. During the target tracking process, the distances and directions of the individual sensor nodes from the target are different, and the measured values of each sensor node contribute differently to the target state estimation. Therefore, in this paper, we comprehensively discuss the above problems, and propose a distributed particle filter algorithm based on Grubbs criterion and mutual information entropy weighted fusion.

The rest of the article is organized as follows. In Section II, The network model, the target motion model and the observation model are presented. Section III gives the detailed description of the proposed algorithm. The performance index of the target tracking system is introduced in Section IV. In section V, simulation results are presented to verify the effectiveness of the proposed method. The conclusion is drawn in Section VI.

II. THE TARGET TRACKING PROBLEM OF UNDERWATER WISELESS SENSOR NETWORKS

A. UNDERWATER TARGET TRACKING

Underwater target tracking is a process of estimating the state of the moving target by using some sensors. Acoustic sensors are usually used to obtain the observed data of the target, and these related target observation data contain uncertain interference. The features of the target generally include the number, the size, the shape, the coordinates, the speed, and the acceleration of the target. The process of the target tracking generally includes five modules: detection module, node selection module, routing module, prediction module, and positioning module [14]. The process of target tracking is shown as Fig. 1.

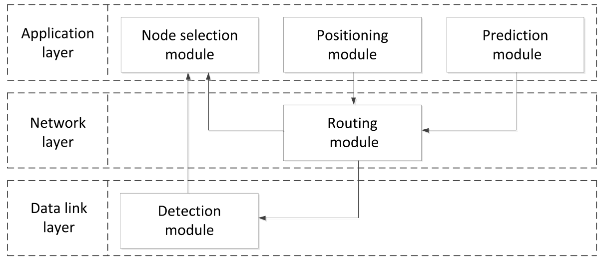

FIGURE 1. Architecture diagram of the target tracking process.

The task of the detection module is to determine whether the target appears its monitoring area. Since the energy carried by the sensors is limited, the sensor nodes periodically detect whether the target appears within the detection range to save the energy consumption of the network. The task of the node selection module is to select the appropriate sensor nodes for observing the status information of the target. The task of the positioning module is to estimate the location of the target by using the perceptual information obtained by the selected most appropriate sensor nodes. The task of the prediction module is to collect the current and previous target state information through the sensor node and then use the prediction algorithm to estimate the target state information at next moment. The task of the routing module is to choose a highly efficient and feasible routing algorithm to pass the obtained target state information to the corresponding cluster head or base station.

The study of this paper mainly focuses on the node selection module and prediction module in the process of the target tracking. First, due to the limitations of centralized estimation method, such as large amount of calculation, constraints of network structure and poor robustness, this paper adopts distributed computing mode and uses the exchange and coordination of local measurement information between sensor nodes to complete the state estimation of the target. To further improve the target tracking accuracy and reduce the energy consumption of the network, when the target enters an area, the sensor nodes and cluster heads in this area are activated and the remaining nodes are in the dormant state. Second, the target information obtained by the sensor nodes is analyzed and verified through the Grubbs criterion, by which the interference information and the error information are eliminated. Then, the mutual information entropy between the measured data obtained by the sensor nodes and the target state are used as the weighting factor of the importance weight of the particle filter algorithm. Eventually, the particle filter algorithm is used to track and predict the target state.

B. UNDERWATER SENSOR NETWORK MODEL

Assume that there are a large number of sensor nodes randomly anchored in the underwater monitoring area S. Each sensor node is equipped with an acoustic sensor and evenly distributed in the monitoring area with the density of

ρ per m^3. The maneuvering target moves within the monitoring area S. According to the characteristics of the monitoring area and the target, the monitoring area is divided into several small areas. All sensor nodes in each small area constitute a cluster. In this paper, the cluster heads (CH) is deployed in the center of each small area, and one-hop communication can cover all the distances between cluster head and sensor nodes within the cluster. The base station is deployed on the water surface. The horizontal signal transceiver is mainly used for communication between the sensor nodes and the cluster heads, and the vertical signal transceiver is mainly used for communication between the cluster heads and the water surface base station.

C. TARGET STATE MODEL

Assuming that there is only one maneuvering target moving within the underwater three-dimensional space [15], the dynamic system can be represented by the state space model, and we adopt the uniform velocity turning model [16], [17]. The target moving state of the tracking system is given by formula (1).

$$X_k = F \cdot X_{k-1} + Q \cdot W_{k-1} \tag{1}$$

where X_k is the target state at time k, and its state vector is presented as $\left(x_{k,x}, v_{k,x}, y_{k,y}, v_{k,y}, z_{k,x}, v_{k,z}, a_{k,x}, a_{k,y}, a_{k,z}\right)$. $(x_{k,x}, y_{k,y}, z_{k,z})$ are the position of the target at the time k. $(v_{k,x}, v_{k,y}, v_{k,z})$ are the corresponding velocities in x, y and z coordinates, and $\left(a_{k,x}, a_{k,y}, a_{k,z}\right)$ are the corresponding acceleration in x, y and z coordinates. Also, the process noise W_{k-1} is always assumed to be Gaussian with zero mean. The state transition matrix F and the process noise variance matrix Q are given as follows

$$F = \begin{bmatrix} I_{3\times3} & \dfrac{\sin(\omega T)}{\omega} \times I_{3\times3} & \dfrac{1-\cos(\omega T)}{\omega^2} \times I_{3\times3} \\ 0_{3\times3} & \cos(\omega T) \times I_{3\times3} & \dfrac{\sin(\omega T)}{\omega} \times I_{3\times3} \\ 0_{3\times3} & -\omega \sin(\omega T) \times I_{3\times3} & \cos(\omega T) \times I_{3\times3} \end{bmatrix} \tag{2}$$

$$Q = \begin{bmatrix} T^2/4 & 0 & 0 \\ T/2 & 0 & 0 \\ 0 & T^2/4 & 0 \\ 0 & T/2 & 0 \\ 0 & 0 & T^2/4 \\ 0 & 0 & T/2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{3}$$

where T is the sampling interval and ω is the turning rate, $I_{3\times3}$ represents a 3×3 unit matrix.

D. TARGET MEASUREMENT MODEL

When the target enters the monitoring area, the sensor nodes distributed in the network will detect the signal from the target. Each sensor node is equipped with an acoustic sensor in the sensor network. The measurement model of the acoustic sensor [18], [19] is given as formula (4).

$$Z_k^j = \frac{S_k}{\left(x_k - x^j\right)^2 + \left(y_k - y^j\right)^2 + \left(z_k - z^j\right)^2} + n_k^j \tag{4}$$

where Z_k^j denotes the signal power measured by the *j-th* sensor at time k. (x_k, y_k, z_k) are the position of the target at time k, and $\left(x^j, y^j, z^j\right)$ are the position of the *j-th* sensor at the time k. S_k denotes the target's sound pressure of source-level. $n_k^j \sim N\left(0, R_k^j\right)$ is the measurement noise. In this paper, we assume that the observation processes of the sensor nodes are independent each other, and the cluster heads know the position coordinates of each sensor node in the cluster.

III. THE PROPOSED ALGORITHM

In this paper, we proposed an algorithm based on distributed particle filter with Grubbs criterion and mutual information entropy. Firstly, the Grubbs criterion method is inducted to test and analyze the data measured by the sensor nodes, thus the abnormal data can be eliminated. Secondly, a dynamic weighting factor based on mutual information entropy is inducted in the process of calculating the importance weight. The detailed process of the algorithm is given as follows.

A. THE Grubbs CRITERION

The Grubbs criterion is a judgment method for abnormal data obeying a normal distributed sample or closely obeying a normal distributed sample in case of an unknown population standard deviation [20]. Since the Grubbs criterion not only considers the times of measurement, but also considers the different confidence levels, it has strong ability of inspection and identification. First, it is used to analyze the measured data to find and eliminate the abnormal data in the raw data, relatively reduces the data which are far away from their real values, and basically ensures that the remaining data approximately obeys the normal distribution. Then, the mutual information entropy between the measured value and the target state is used to determine the weight of the nodes status, and this can have the weight have more objectivity instead of being given randomly. Here we assume that the network sensor nodes are the same kind of nodes with same kinds of sensors to detect the target at different positions.

Assume that, during the target tracking process in underwater WSN, there are M sensor nodes in the small area where the target is located at time k. A set of data measured by sensor nodes are recorded as $Z_k^1, Z_k^2, \ldots, Z_k^M$. The mean value of the set of data is $\overline{Z_k}$. The variance is σ_k, and the residual error is given by formula (5).

$$v_k^j = Z_k^j - \overline{Z_k}, \quad j = 1, 2, \ldots, M \tag{5}$$

The data obtained by the sensor nodes participating in the measurement task at time k are standardized as formula (6).

$$S_k = \frac{\left|Z_k^i - \overline{Z_k}\right|}{\sigma_k} \tag{6}$$

where S_k obeys a certain probability distribution, and its probability distribution density function is $f(Z_k)$, then there exists:

$$p\left\{\frac{\left|Z_k^j-\overline{Z_k}\right|}{\sigma_k}<\lambda_\alpha(M)\right\}=1-\alpha \tag{7}$$

$$p\left\{\left|Z_k^j-\overline{Z_k}\right|>\lambda_\alpha(M)\,\sigma_k\right\}=\alpha \tag{8}$$

Substituting (5) into (8), we obtain

$$p\left\{\left|v_k^j\right|>\lambda_\alpha(M)\,\sigma_k\right\}=\alpha \tag{9}$$

where $\lambda_\alpha(M)$ is generally called Grubbs coefficient, and it can be obtained by looking up the table. α is the given confidence level. Since the value of α is very small, $\left|v_k^j\right|>\lambda_\alpha(M)\,\sigma_k$ occurs with a small probability. Moreover, if there are few sensor nodes participating in the measurement task at time k, it is almost impossible that $\left|v_k^j\right|>\lambda_\alpha(M)\,\sigma_k$ could occur [21], [22].

If $\left|v_k^j\right|>\lambda_\alpha(M)\,\sigma_k$ holds, generally it could be thought that it is caused by a coarse error, which indicates that the data measured by the sensor is an abnormal value in the case of large probability, so that it probably could be eliminated.

B. CALCULATING THE MUTUAL INFORMATION ENTROPY BETWEEN THE MEASURED VALUE OF THE SENSOR NODE AND THE TARGET STATE

Entropy is a basic concept in information theory and it represents the amount of information in a random variable. Mutual information entropy is used to represent the relationship between information, and it is a measure of the statistical correlation between two random variables. In the application of underwater WSNs, the mutual information entropy can be used to measure the amount of information that the sensor nodes detect to the target state, and it also means the amount of target information which the sensor nodes can provide. The definition of the mutual information entropy between the measured value from the sensor nodes and the target state is given follows.

Definition 1: The mutual information entropy between the measured value of the *j-th* sensor node and the target state at time k can be approximately expressed as follows.

$$\begin{aligned}I\left(X_k,Z_k^j\right)&=H\left(Z_k^j\right)-H\left(Z_k^j\,|X_k\right)\\&=-\sum_{Z_k^j}\left\{\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\}\\&\quad\times\left\{\log\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\}\\&\quad+\sum_{Z_k^j}\left\{\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right).\log p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\}\end{aligned} \tag{10}$$

where $I(.)$ represents the mutual information entropy. $H(.)$ represents information entropy. $X_{k|k-1}^i$ is the $i-th$ predicted particle, and all particles have equal weight as $1/N$. We can make the proving as follows.

Proof: According to the definition of mutual information entropy and the nature of mutual information entropy, the mutual information between the measured value of the *j-th* sensor node and the target state at time k is expressed as formula (11).

$$I\left(X_k,Z_k^j\right)=H(X_k)-H\left(X_k\left|Z_k^j\right.\right)=H\left(Z_k^j\right)-H\left(Z_k^j\,|X_k\right) \tag{11}$$

Considering the definition of entropy, $H\left(Z_k^j\right)$ is expressed as Eq. (12).

$$H\left(Z_k^j\right)=-\sum_{Z_k^j}p\left(Z_k^j\right)\log p\left(Z_k^j\right) \tag{12}$$

Using the particle to predict $p\left(Z_k^j\right)$, we can obtain Eq. (13).

$$p\left(Z_k^j\right)=\int_{X_k}p\left(Z_k^j\,|X_k\right)p(X_k)\,d_{X_k}\approx\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right) \tag{13}$$

Substituting (13) into (12), $H\left(Z_k^j\right)$ can be rewritten as Eq. (14).

$$\begin{aligned}H\left(Z_k^j\right)=&-\sum_{Z_k^j}\left\{\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\}\\&\times\left\{\log\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\}\end{aligned} \tag{14}$$

According to the definition of the conditional entropy, the conditional entropy between the measured value of the *j-th* sensor node and the target state at time k is calculated as formula (15).

$$H\left(Z_k^j\,|X_k\right)=-\sum_{Z_k^j}\int_{X_k}p\left(Z_k^j,X_k\right)\log p\left(Z_k^j\,|X_k\right)d_{X_k} \tag{15}$$

The definition of the joint probability is shown as formula (16).

$$p\left(Z_k^j,X_k\right)=p\left(Z_k^j\,|X_k\right)p(X_k) \tag{16}$$

Substituting (16) into (15), we can obtain Eq. (17).

$$H\left(Z_k^j\,|X_k\right)=-\sum_{Z_k^j}\int_{X_k}p\left(Z_k^j\,|X_k\right)p(X_k)\log p\left(Z_k^j\,|X_k\right)d_{X_k} \tag{17}$$

Using particle to predict $H\left(Z_k^j|X_k\right)$ as well, we obtain the approximation of $H\left(Z_k^j|X_k\right)$ as Eq. (18).

$$H\left(Z_k^j|X_k\right) = -\sum_{Z_k^j}\frac{1}{N}\sum_{i=1}^{N}\left\{p\left(Z_k^j\left|X_{k|k-1}^i\right.\right).\log p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\} \tag{18}$$

Substituting (14) and (18) into (11), the mutual information entropy between the measured value of the sensor nodes and the target state can be expressed as follows.

$$\begin{aligned} I\left(X_k, Z_k^j\right) &= H\left(Z_k^j\right) - H\left(Z_k^j|X_k\right) \\ &= -\sum_{Z_k^j}\left\{\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\} \\ &\quad\times\left\{\log\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\} \\ &\quad+\sum_{Z_k^j}\left\{\frac{1}{N}\sum_{i=1}^{N}p\left(Z_k^j\left|X_{k|k-1}^i\right.\right).\log p\left(Z_k^j\left|X_{k|k-1}^i\right.\right)\right\} \end{aligned} \tag{19}$$

(**Proof completed**)

The mutual information entropy between the measurement data of the sensor nodes and the target state can effectively measure the correlation between the two variables, which is the effective information of the target that the sensor nodes can provide. The greater the mutual information entropy is, the more target information the sensor nodes can provide.

C. DISTRIBUTED PARTICLE FILTER TARGET TRACKING ALGORITHM BASED ON GRUBBS CRITERION AND MUTUAL INFORMATION ENTROPY

Particle filtering can be used as an estimation method based on Monte Carlo and recursive Bayesian estimation. The essence is to approximate the posterior probability distribution using a set of randomly sampled particles with corresponding weights [23]. It is not affected by linear errors and Gaussian noise, so it has better performance than the Kalman filter and the extended Kalman filter for the nonlinear and non-Gaussian state space models. The particle filter algorithm needs to be recursively calculated by two steps of predicting and updating.

The prediction process is to use the prior probability density of the system model to predict the state, that is, to guess the future state through the existing prior knowledge. If the initial probability density of the known state is $p(X_0|Z_0) = p(X_0)$, $p(X_k|Z_{1:k-1})$ can be obtained from the probability density of the previous moment $p(X_{k-1}|Z_{1:k-1})$. The calculation formula can be derived as follows.

$$\begin{aligned} p(X_k|Z_{1:k-1}) &= \int p(X_k, X_{k-1}|Z_{1:k-1})d_{X_{k-1}} \\ &= \int p(X_k|X_{k-1}, Z_{1:k-1})p(X_{k-1}|Z_{1:k-1})\,d_{X_{k-1}} \\ &= \int p(X_k|X_{k-1})p(X_{k-1}|Z_{1:k-1})\,d_{X_{k-1}} \end{aligned} \tag{20}$$

where $Z_{1:k-1}$ is the observation vector at the moment from 1 to $k-1$.

The update process is to use the latest measured values to correct the prior probability density to obtain the posterior probability density, that is, to correct the previous guess. The posterior probability $p(X_k|Z_{1:k})$ can be obtained from $p(X_k|Z_{1:k-1})$. The posterior probability calculation can be derived as follows.

$$\begin{aligned} p(X_k|Z_{1:k}) &= \frac{p(Z_k|X_k, Z_{1:k-1})\,p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \\ &= \frac{p(Z_k|X_k)\,p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \end{aligned} \tag{21}$$

where the normalization constant $p(Z_k|Z_{1:k-1})$ can be obtained as Eq. (22).

$$p(Z_k|Z_{1:k-1}) = \int p(Z_k|X_k)\,p(X_k|Z_{1:k-1})d_{X_k} \tag{22}$$

In practical applications, the samples cannot be directly obtained by sampling from the posterior probability distribution, so the importance sampling method is inducted, which improves the sampling frequency. Extracting N sample particles $\left\{X_k^i, i = 1, 2, \ldots, N\right\}$ from the importance probability density $q(X_k|Z_{1:k})$, and the posterior probability density function at time k can be approximately calculated as formula (23).

$$p(X_k|Z_{1:k}) \approx \sum_{i=1}^{N}\omega_k^i\delta\left(X_k - X_k^i\right) \tag{23}$$

where ω_k^i is calculated as

$$\omega_k^i \propto \frac{p\left(X_k^i|Z_{1:k}\right)}{q\left(X_k^i|Z_{1:k}\right)} \tag{24}$$

Since, the importance probability density function can be decomposed into as follows.

$$q(X_k|Z_{1:k}) = q(X_k|X_{k-1}, Z_{1:k})\,q(X_{k-1}|Z_{1:k-1}) \tag{25}$$

Also, the posterior probability density function $p(X_k|Z_k)$ can be decomposed into as follows.

$$\begin{aligned} p(X_k|Z_{1:k}) &= \frac{p(Z_k|X_{0:k}, Z_{1:k-1})\,p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \\ &= \frac{p(Z_k|X_k, Z_{1:k-1})\,p(X_k|X_{k-1}, Z_{1:k-1})\,p(X_{k-1}|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \\ &= \frac{p(Z_k|X_k)\,p(X_k|X_{k-1})\,p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \\ &\propto p(Z_k|X_k)\,p(X_k|X_{k-1})\,p(X_{k-1}|Z_{1:k-1}) \end{aligned} \tag{26}$$

Thus, we can substitute (25) and (26) into (24), the recursive formula for the weight importance of the particles can be expressed as formula (27).

$$w_k^i \propto \frac{p\left(X_k^i \left|Z_{1:k}\right.\right)}{q\left(X_k^i \left|Z_{1:k}\right.\right)} = \frac{p\left(Z_k \left|X_k^i\right.\right) p\left(X_k^i \left|X_{k-1}^i\right.\right) p\left(X_{k-1}^i \left|Z_{1:k-1}\right.\right)}{q\left(X_k^i \left|X_{k-1}^i, Z_{1:k}\right.\right) q\left(X_{k-1}^i \left|Z_{1:k-1}\right.\right)} = w_{k-1}^i \frac{p\left(Z_k \left|X_k^i\right.\right) p\left(X_k^i \left|X_{k-1}^i\right.\right)}{q\left(X_k^i \left|X_{k-1}^i, Z_{1:k}\right.\right)} \tag{27}$$

Since, $1/p\left(Z_k \left|Z_{1:k-1}\right.\right)$ is lost in the derivation process of formula (27), the importance weight should be normalized as follows.

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^{N} w_k^i} \tag{28}$$

Assume that the importance probability density function satisfies

$$q\left(X_k \left|X_{k-1}, Z_{1:k}\right.\right) = p\left(X_k \left|X_{k-1}\right.\right) \tag{29}$$

Substituting (29) into (27), the importance weight calculation formula can be expressed as follows.

$$w_k^i = w_{k-1}^i p\left(Z_k \left|X_k^i\right.\right) \tag{30}$$

In the above importance sampling process, the particle will meet the degradation problem, and this phenomenon is usually unavoidable. Therefore, the resampling method needs to be inducted. The basic principle of resampling is to eliminate the particles with small weights and duplicate the particles with large weights for keeping the number of particles unchanged. Then the new particles will be assigned the same weight as $1/N$.

Since the weight of each particle is $1/N$ after the particles are updated, formula (30) can be rewritten as formula (31).

$$w_k^i \propto p\left(Z_k \left|X_k^i\right.\right) \tag{31}$$

The above equation is generally called SIR (Sampling Importance Resampling, SIR) calculation formula. However, in the process of calculating the importance weight, it is not considered that the contribution of each sensor node to the estimation result of target state is different, and this affects the tracking accuracy of the entire tracking system. Therefore, a dynamic weighting factor β_k^i is introduced in this paper. When the contribution of the measured value from sensor node to the target state estimation is larger, the corresponding weighting factor is larger, and when the contribution of the measured value to the target state estimation is smaller, the corresponding weighting factor will be smaller as well. Mutual information entropy can effectively measure the correlation between two variables, that is, it can measure the effective information about the target provided by sensor nodes. The larger the mutual information entropy is, the larger the amount of information about the target provided by sensor node will be, and the corresponding weight coefficient of sensor node is larger. Therefore, the weight coefficient corresponding to the sensor node is equivalent to the information volume about the target provided by the sensor node. In this paper, the mutual information entropy between the measured value of sensor nodes and the target state is used as the dynamic weighting factor for calculating the importance weight of particle filter, which can improve the target tracking accuracy effectively.

Definition 2: At time k, the importance degree of the measured value of the *j-th* sensor node to determine the target state, that is, the weighting factor corresponding to the sensor node, is defined as formula (32).

$$\begin{cases} \beta_k^j = \dfrac{I_k^j}{\sum_{j=1}^{M_s} I_k^j} \\ \sum_{j=1}^{M_s} \beta_k^j = 1, \quad j = 1, 2, 3, \ldots M_S \end{cases} \tag{32}$$

where I_k^j represents the mutual information entropy between the *j-th* sensor node and the target state at time k. β_k^j indicates the corresponding weight of the *j-th* sensor node participating in the measurement task at time k.

Definition 3: The mutual information entropy weighting factor is introduced in (31) to obtain an improved weighting formula for SIR particle filtering, and the importance weight of the $i-th$ particle at time k is calculated as formula (33).

$$\omega_k^i = p\left(Z_k^1, Z_k^2, \ldots, Z_k^{M_s} \left|X_k^i\right.\right) = \prod_{j=1}^{M_s} p\left(Z_k^j \left|X_k^i\right.\right)^{\beta_k^j} \tag{33}$$

However, before each resampling, the effective particle number at current moment needs to be judged to decide whether to perform resample. The effective number of the particle is used to measure the degree of degradation of particle weights, which is presented as formula (34).

$$\hat{N}_{eff} = \frac{N}{\sum_{i=1}^{N} \left(w_k^i\right)^2} \tag{34}$$

where $\hat{N}_{eff}$ represents the approximate value of the number of effective particles at current time, and N_{th} is an appropriate threshold (N_{th} generally takes $2N/3$). The judgment needs to be performed in each iteration. If $\hat{N}_{eff}$ is less than the threshold N_{th}, the resampling is performed. If not, it is not performed.

D. THE ALGORITHM FLOW

In the target tracking process, only the sensor nodes and cluster heads in the small area where the target is located can be awakened at each moment, and the remaining sensor nodes are in the dormant state. The measured data from the sensor nodes participating in the observation task at time k are analyzed and verified by the Grubbs criterion for eliminating the abnormal data. The activated cluster head at the current time receives the processed observation data from the corresponding sensor nodes and runs the improved SIR particle filter. Once the target leaves the current small area, the cluster head node passes the target state information at the last sampling instant to the next activated cluster head.

The pseudocode of the proposed algorithm is as **Algorithm 1.**

Algorithm 1 Distributed Particle Filter Algorithm Based on Grubbs and Mutual Information Entropy Weighted

–N: the number of particle
–M_s: the number of the independent measurement data obtained by the CH after removing abnormal data
–K_A: the last sampling moment of the target in the area of CH_A
–K: the moment of the target leaving the monitoring area
if $k = 0$
then Initialize the cluster head node
for $i = 1, 2, \ldots, N$ do
Draw particle X_k^i from the prior target state $p(X_0)$
end for
end if
While $k < K$ **do**
for $k \leftarrow 1$ to K_A **do**
Remove abnormal data by Grubbs, and getting M_{sa} independent measurement data
for i $\leftarrow 1$ to N **do**
Sample by $X_k^i \sim p\left(X_{k-1} \left| X_k^i\right.\right)$
end for
for $j \leftarrow 1$ **to** M_{sa} **do**
Update the fusion weight vector β_k by (10) and (32)
end for
for $i \leftarrow 1$ to N **do**
Update the importance weights by (10), (32) and (33)
Normalize the importance weights by (28)
Resampling;
end for
Estimate the state $\hat{X}_k$ and covariance P_k:
$\hat{X}_k^a = \sum_{i=1}^{N} \omega_k^i X_k^i$; $P_k^a = \sum_{i=1}^{N} \omega_k^i \left(X_k^i - \hat{X}_k\right)\left(X_k^i - \hat{X}_k\right)^T$
Pass $\hat{X}_k^a$ and P_k^a to the next new cluster head;
end for
The new cluster head node does the following steps:
for $i \leftarrow 1$ to N **do**
Draw particle $X_k^i \sim N\left(\hat{X}_k^a, P_k^a\right)$;
end for
repeat the steps done by the previous cluster head node;
end

IV. PERFORMANCE INDICATORS

Target tracking algorithm of underwater WSNs requires to consider multiple performance metrics, such as tracking accuracy, tracking response time, and energy consumption. An ideal target tracking system has high tracking accuracy, less tracking response time and energy loss. The tracking response time mainly reflects the real-time performance of the target tracking system, which is related to the calculation time of the prediction algorithm and the routing method of the tracking system. The tracking accuracy and energy consumption should be compromised. For example, if the tracking accuracy of the system is improved, more measurement data of the sensor nodes are needed, which leads to more energy consumption of transmitting more information.

A. TRACKING ACCURACY

Tracking accuracy mainly reflects the tracking effect of the target. In this paper, we adopt the Root Mean Square Error (RMSE) to reflect the tracking accuracy of the target [24]. The RMSE of the target position is defined as formula (35).

$$RMSE = \sqrt{\frac{1}{MC}\sum_{m=1}^{MC}\left(\begin{array}{l}\left(x_{k,m}-\widehat{x}_{k,m}\right)^2+\left(y_{k,m}-\widehat{y}_{k,m}\right)^2\\+\left(z_{k,m}-\widehat{z}_{k,m}\right)^2\end{array}\right)} \tag{35}$$

where MC represents the number of simulations times, and $\left(x_{k,m}, y_{k,m}, z_{k,m}\right)$, $\left(\widehat{x}_{k,m}, \widehat{y}_{k,m}, \widehat{z}_{k,m}\right)$ are the true position and the estimated position of the target at time k in the m-th simulation respectively.

B. TRACKING RESPONSE TIME

The tracking response time, including the computation time of the algorithm and data transmission time, indicates the time required for underwater WSNs to obtain the target state information [25]. It is assumed that the data transmission time of each algorithm is the same at each moment. The tracking response time at time k is determined by the computation time of the algorithm.

C. ENERGY CONSUMPTION

To quantitatively calculate the energy consumption of underwater sensor nodes, we adopt the network energy consumption model in [26], [27].

The energy consumption for sending a b - bit packet is defined as formula (36), and the energy consumption for receiving a b - bit packet is defined as formula (37).

$$E_{\text{send}}(b, d) = bP_o A(d) \tag{36}$$

$$E_{receive}(b) = bP_\tau \tag{37}$$

where P_0 is the power level needed by the input of the receiver. P_τ is a constant parameter depending on the receiver devices. d is the communication distance. The energy attenuation part $A(d)$ is defined as formula (38).

$$A(d) = d^{\mu} a^{d} \tag{38}$$

where μ is the energy spreading factor (1 for the cylinder model, 1.5 for the actual model, and 2 for the sphere model), and d is the communication distance. $a = 10^{\alpha(f)}/10$ is determined by the absorption coefficient $\alpha(f)$.

$$\alpha(f) = \frac{0.11f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75 \times 10^{-4} f^2 + 0.003 \tag{39}$$

where f is the frequency and the unit is kHz.

It can be seen from the network energy consumption model that the network energy consumption is related to the communication distance and the amount of transmission data. In this paper, it is assumed that the amount of data transmission from each sensor node is the same at time k, thus we only consider the relationship with the communication distance, and the model parameters are set as: $P_O = 2w$, $P_\tau = 20mw$, $f = 50kHz$ [28].

V. SIMULATION AND ANALYSIS

In this section, simulations are carried out in the 3D scenario to verify the effectiveness of the proposed algorithm. The importance weight of the standard SIR is calculated using the average weighted (AW) fusion [29], which doesn't take into account the difference in the amount of target information provided by each sensor node. In [30], the authors proposed a weighted fusion algorithm based on analytic hierarchy process (AHPW), which needs to do the consistency check to the constructed contrast matrix. If the consistency ratio is less than 0.1, the weights corresponding to each sensor nodes are reasonably allocated. Otherwise, the decision maker will be asked to reconstruct the comparison matrix until an acceptable level of consistency is achieved. In [31], the authors proposed a new improved algorithm by introducing RSSI distance weighted centroid algorithm based on EKF algorithm (REKF). To check and analyze the tracking performance of the proposed algorithm more comprehensively, these three representative algorithms and the proposed GMIEW algorithm are studied to compare the impact in terms of the observed noise variance, sensor density and the number of small sub-network area.

A. SIMULATION SCENARIO AND PARAMETER SETTINGS

It is assumed that the size of the monitoring area of underwater WSN is $100 \times 100 \times 100$ m^3. The monitoring area is divided into eight small areas with size $50 \times 50 \times 50$ m^3. The whole region is divided into eight clusters. CH1 (25, 25,25) , CH2 (75, 25,25), CH3 (25, 75,25), CH4 (75,75,25), CH5 (25,25,75), CH6 (75,25,75), CH7 (25,75,75) and CH8 (75,75,75) are the cluster head nodes of each small area. BS (100,100,100) is the water surface base station. The simulation scenario is shown as Fig.3. The sensor nodes are randomly deployed throughout the monitoring area and the target moves in 3D space. The target makes a uniform turning motion in the monitoring area, and the motion model of the maneuvering target is adopted as introducing in Section II. Under this scenario, the proposed algorithm will be simulated and compared with AW, AHPW and REKF algorithms. In the simulation experiment, we tested the average position RMSE, response time of the four algorithms, and the energy consumption of the network, respectively. The average position RMSE and response time are used as indicators to measure the comprehensive performance of the tracking algorithm. The detailed parameters setting in target tracking algorithm simulations are shown as TABLE 1.

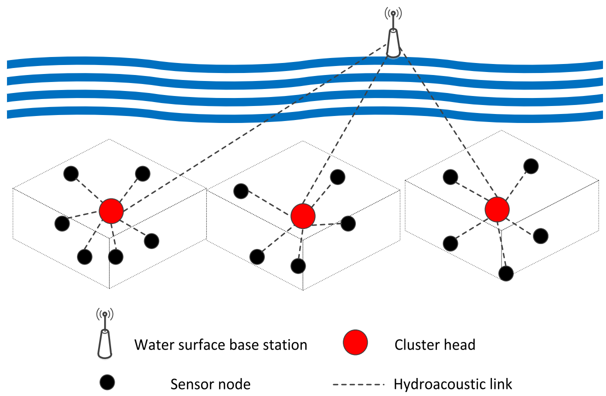

FIGURE 2. Underwater sensor network model.

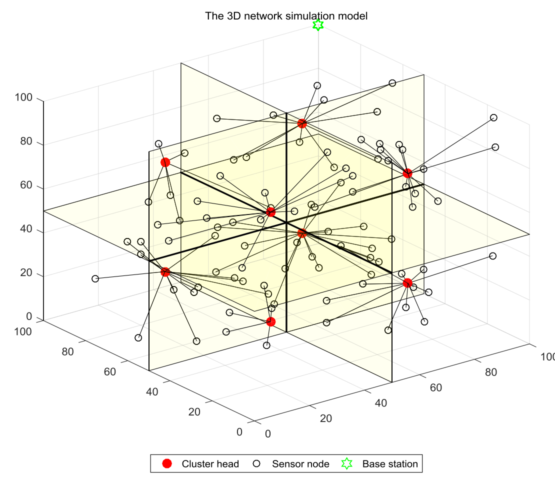

FIGURE 3. 3D network simulation scenario.

TABLE 1. Parameter setting in target tracking algorithm simulations.

Simulation parameter			
Target initial position (m)	(0,60,80)	Target initial speed (m/s)	(15,-20,4)
Target initial acceleration (m/s^2)	(5,6,-1)	Sampling interval (s)	1
Number of particles(per)	2000	Monitoring time (s)	20
acoustic sensor density(per/m^3)	0.00008	Process noise variance	0.1
Number of simulations	100	Target signal energy S	5000
Turning rate ω	0.1		

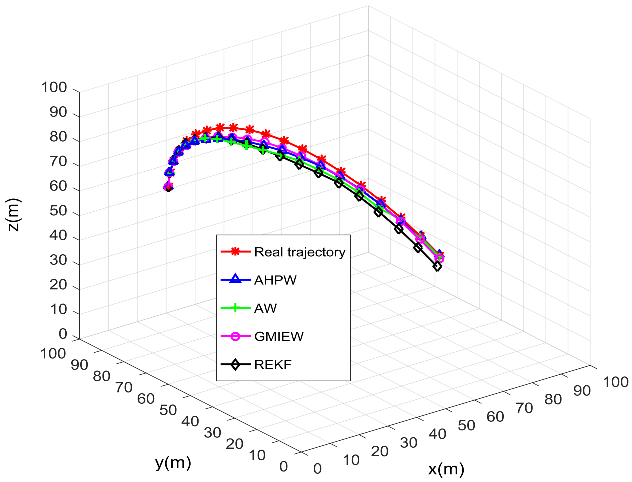

FIGURE 4. Observation noise variance = 0.36, the different tracking trajectories of the algorithms under the scenario of a turning motion.

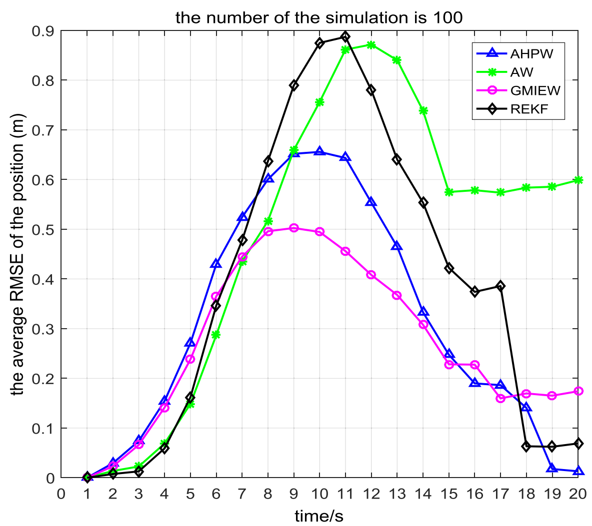

FIGURE 5. Observation noise variance = 0.36, the average position RMSE of the different algorithms under the scenario of a turning motion.

B. SIMULATION RESULTS AND ANALYSIS

1) INFLUENCE OF OBSERVED NOISE VARIANCE ON TARGET TRACKING ALGORITHM

To study the stability of the target tracking algorithms under different conditions, this paper analyzes the performance of the algorithms by changing the observed noise. Firstly, we set the initial conditions to an ideal state with the small observed noise, and then gradually increase the observation noise to compare the performance of the three different algorithms. In order to compare the performance of the algorithm, we adopt the average position RMSE described in Eq.(35) to test. Under the simulation conditions described in Section *A*, the observed noise variance is taken as 0.36, 2, and 5 respectively. To compare the simulation results more intuitively, the tracking trajectories obtained by the three algorithms are shown as Fig. 4, Fig. 6 and Fig. 8. The average position RMSE is shown as Fig. 5, Fig. 7 and Fig. 9.

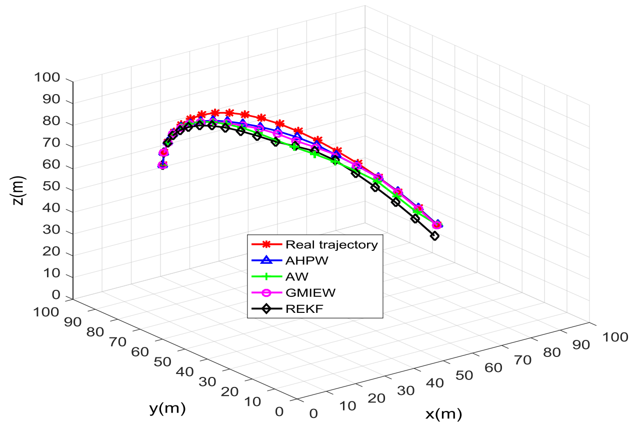

FIGURE 6. Observation noise variance = 2, the different tracking trajectories of the algorithms under the scenario of a turning motion.

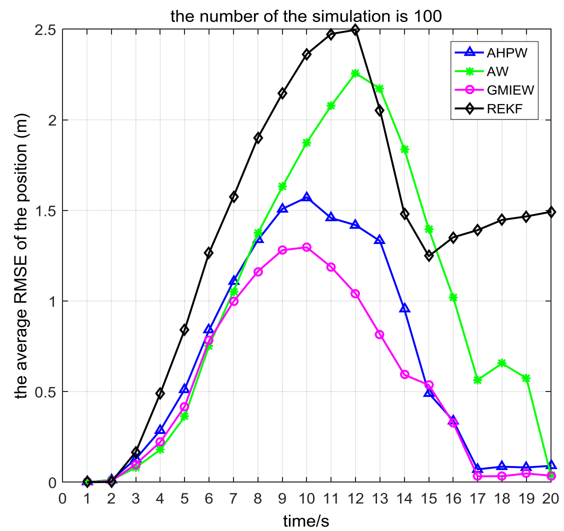

FIGURE 7. Observation noise variance = 2, the average position RMSE of the different algorithms under the scenario of a turning motion.

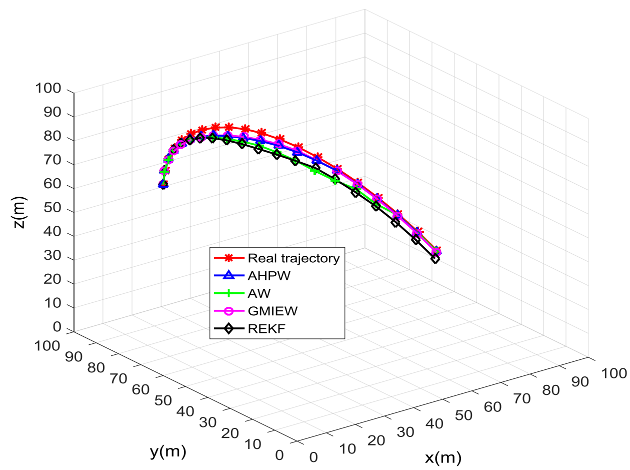

FIGURE 8. Observation noise variance = 5, the different tracking trajectories of the algorithms under the scenario of a turning motion.

The influence of observation noise on target tracking accuracy is not negligible. It can be clearly seen from Fig. 4-9 that, as the variance of the observation increases, the tracking

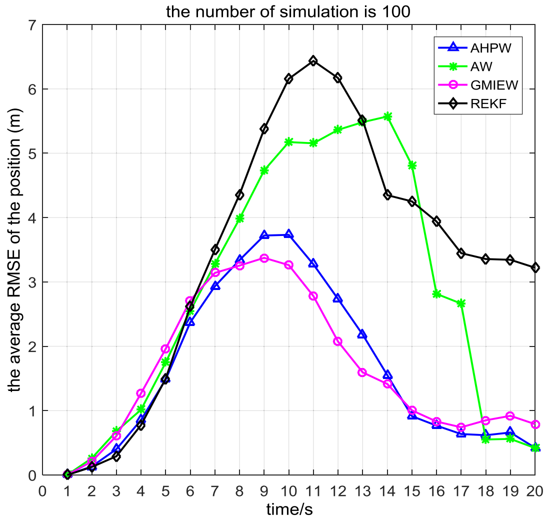

FIGURE 9. Observation noise variance = 5, the average position RMSE of the different algorithms under the scenario of a turning motion.

TABLE 2. Average tracking response of the three algorithms.

Tracking algorithm	Average tracking response time（s）
REKF	0.0911
AW	0.1425
AHPW	0.3642
GMIEW	0.5503

accuracy of the different algorithms decreases to a certain extent, and the target tracking error increases to a certain extent. It can be seen from Fig. 5, 7, and 9 that the tracking error of the three algorithms is small at the initial stage of target tracking. As time goes on, the tracking error of the target reaches the maximum at the target turning. The algorithm is closer to the true trajectory of the target regardless of the value variance of the observed noise, and the average position RMSE of the proposed algorithm is always smaller than the other three algorithms. It indicates that the proposed algorithm can effectively perform target tracking and has better robustness, which greatly improves the target tracking accuracy of the system.

2) REAL-TIME PERFORMANCE OF THREE TRACKING ALGORITHMS

To test the real-time performance of the three algorithms, the sensor density is set as 0.00008 per m^3 and the observed noise variance is set as 0.36. The simulation runs 100 times for each experiment on these algorithms. Under the same initial conditions, the average tracking response time of the different algorithms for the target tracking algorithm is shown in Table 2.

It can be seen from TABLE 2 that the average response time of the three algorithms have the similar order of magnitude. Due to the small amount of computation of the REKF algorithm, the average tracking response time of REKF is the shortest. The proposed GMIEW algorithm first needs to

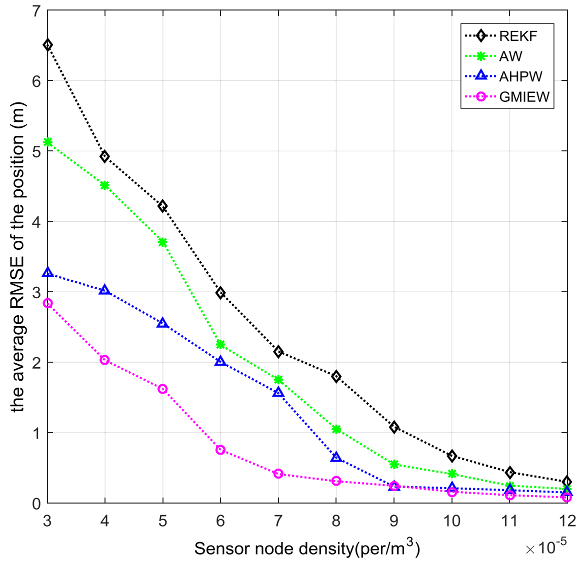

FIGURE 10. The average position RMSE of the different algorithms under the different sensor node densities.

analyze the measurement data from the sensor nodes though Grubbs criterion, and needs to calculate the mutual information entropy between the measured value and the target state of each sensor node, thus the average reflection time of GMIEW is slightly higher than that of the other two algorithms. The average reflection time of AHPW algorithm is shorter than GMIEW and longer than AW. However, considering the tracking accuracy, robustness of the proposed GMIEW, and the increment of the average reflection time is not so large, the proposed GMIEW is still more suitable to be used in underwater target tracking.

3) INFLUENCE OF SENSOR DENSITY ON UNDERWATER SENSOR NETWORK ON TARGET TRACKING

This section mainly analyzes the effect of the different sensor densities on the three tracking algorithms. In the simulation experiment, the observed noise variance is set as 0.36 and the sensor density is taken as 0.00003 to 0.00012. The other parameters are set as the same as TABLE 1. Fig.10 shows the average position RMSE of the different algorithms at different sensor densities.

Fig. 10 shows the average position RMSE comparison of the different algorithms under different sensor nodes densities. The average position RMSEs of these algorithms decrease as the node density increases. As can be seen from Fig.10, the average position RMSE of the three algorithms is gradually reduced with the sensor node's density increasing. When the density increases from 0.00003 to 0.00008, the tracking accuracy is significantly improved. However, when the density increases from 0.00008 to 0.00012, the improvement of tracking accuracy is slower. This indicates that there is a limitation value of ρ, and if is exceeds that ρ, the benefits of using more sensors in tracking performance are very small. Furthermore, as the ρ increases, the amount of computation and communication overhead of the network will

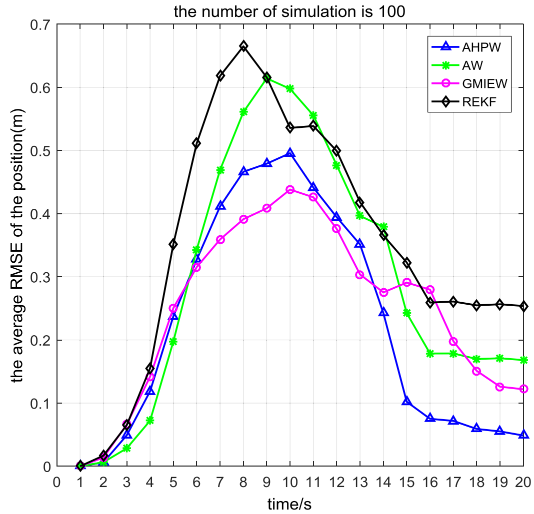

FIGURE 11. **Under the number of small regions = 4, the average position RMSE of three different algorithms under the scenario of a turning motion.**

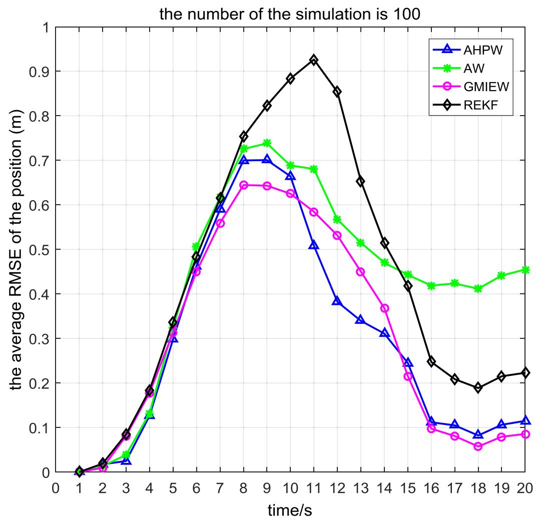

FIGURE 12. **Under the number of small regions = 8, the average position RMSE of three different algorithms under the scenario of a turning motion.**

increase accordingly. Therefore, when designing an underwater tracking WSN, it is necessary to select a balanced value of sensor density of the network on the premise of compromising consumption and performance.

4) INFLUENCE OF THE NUMBER OF SMALL NETWORK REGIONS ON TARGET TRACKING

To test the performance of the underwater tracking sensor network, the observed noise variance is set as 0.36 and the sensor density is set as 0.00008 per m^3. The number of small regions is taken as 4, 8, and 16, respectively. 100 times simulation experiments are performed for the three algorithms. To study the influence of the number of small regions on target tracking, we analyzed the tracking accuracy and network energy consumption of target tracking algorithms under different partition of small regions. The average position RMSE of the three algorithms under different number of small regions is

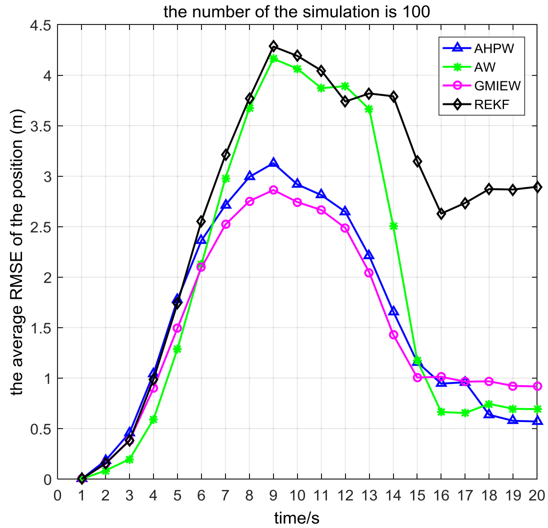

FIGURE 13. **Under the number of small regions = 16, the average position RMSE of three different algorithms under the scenario of a turning motion.**

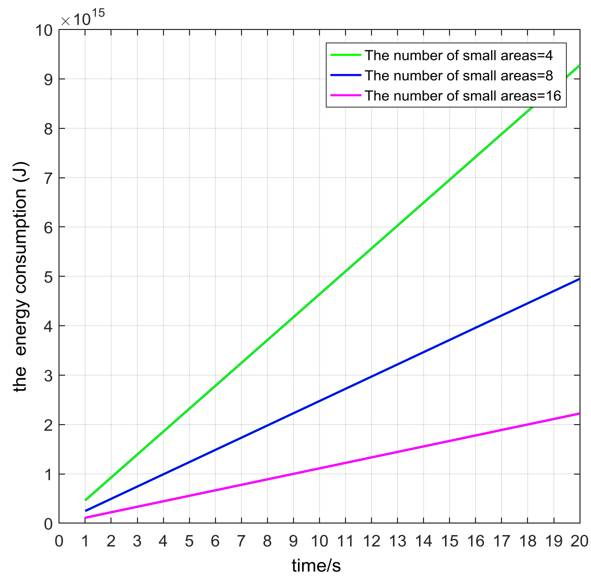

FIGURE 14. **The energy consumption of three different algorithms under different numbers of small regions.**

TABLE 3. **Average position RMSE under different numbers of small regions.**

The number of small regions	Number=4	Number=8	Number=16
Different algorithms	The average position RMSE (m)		
REKF	0.4059	0.9024	2.1761
AW	0.3681	0.6140	1.8513
AHPW	0.0984	0.3325	1.1562
GMIEW	0.0315	0.1526	0.8267

shown in Fig. 11–13, and the network energy consumption is shown in Fig.14. TABLE 3 shows the average position RMSE of the three algorithms with different numbers of small region.

It can be seen from Fig. 11 to Fig. 13 that, as the number of small regions increases from 4 to 16, the average position RMSE of the proposed algorithm is always lower than the other three algorithms. In Table 3, it can be seen intuitively that, as the number of small areas increases, the average position RMSEs of the algorithms will get larger and larger, that is, the target tracking accuracy becomes lower and lower. Fig.14 shows that, as the number of small regions increases, the energy consumption of the network decreases. Obviously, as the number of small regions increases, the target tracking accuracy decreases and the network energy consumption becomes lower. The network energy consumption and the target tracking accuracy are contradictory. Therefore, it is crucial to make a tradeoff between the tracking accuracy and the energy consumption when we use the partition tracking strategies.

VI. CONCLUSION

In this paper, for the problems of the existing anomalous data, the weighted fusion, and the limited energy in underwater WSNs, a distributed particle filter algorithm based on Grubbs criterion and mutual information entropy was proposed. Firstly, during the tracking process, the obtained measurement data will have more correctness by eliminating some interference and error information measured from the sensor nodes. Secondly, we conduct the dynamic weighted factors to weigh the contribution of the measurement data of each sensor node to the target state prediction, which effectively improves the accuracy of the measurement data to the target tracking. Therefore, the tracking accuracy of the target tracking system is improved. The simulation results show that the proposed algorithm has higher tracking accuracy and better robustness than REKF, AW and AHPW algorithms. Increasing the sensor density appropriately can improve the target tracking accuracy. However, considering the amount of calculation and the limited energy of the network, the density of the sensors should not be too large. Furthermore, setting the suitable partition number of small regions of the network according to specific application requirements can result in applicable tradeoff between tracking accuracy and tracking energy consumption.

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