

SPECIFICATION

A WIRELESS SENSOR NETWORK POSITIONING METHOD FOR MARINE SEARCH AND RESCUE BASED ON INFORMATION FUSION

TECHNICAL FIELD

The present disclosure relates to the technical field of marine wireless sensor network node localization, and in particular, to a wireless sensor network positioning method for marine search and rescue based on information fusion.

BACKGROUND

As an important component of marine economy, the development of maritime transportation industry is of vital importance. In order to ensure the safety of maritime transportation, relevant departments have formulated a series of measures to prevent accidents, especially those caused by human factors. However, the maritime environment is complex and changeable, and the occurrence of extreme weather threatens the safety of maritime transportation, such as the Yangtze Star cruise ship accident. When extreme weather causes a marine accident, it is a critical step about how to reduce the loss of lives and property as much as possible. As the last barrier to ensure the safety of lives at sea, Marine Search and Rescue (MSR) can reduce the loss of lives and property to the greatest extent through multi-faceted and multi-sectoral integrated cooperation. At this stage, for marine search and rescue, the search and rescue scope is minimized as much as possible through remote sensing images or based on wind flow to facilitate rescue operations. However, this method is time-consuming and has a large error, which may result in missing the golden period of rescue to a large extent. In order to reduce this defect, by means of good self-organization, expandability, and adaptability of Wireless Sensor Networks (WSNs), the success rate and efficiency of search and rescue may be greatly improved.

However, it is a challenge about how to accurately and efficiently locate a rescue target in a marine search and rescue sensor network. On the one hand, in a highly dynamic maritime environment, the rescue target may move with wind flow, etc., making localization difficult and localization efficiency low. On the other hand, high-latency, low-bandwidth maritime communication channels make localization accuracy poor, moreover, the nonlinear non-Gaussian noise generated by sea wave masking and multi-path effects further increases the localization error. In addition, relying only on a single ranging technology, such as received signal strength (RSS), the

error will increase as the search and rescue range increases due to inherent defects in the technology. The existing localization technology does not have a good solution to the above three problems of marine search and rescue wireless sensor networks, cannot take into account the accuracy and efficiency of localization well, and cannot achieve real-time, efficient and accurate localization of the target to be rescued.

SUMMARY

An object of the present disclosure is to provide a wireless sensor network positioning method for marine search and rescue based on information fusion to solve the problem that the localization accuracy of the marine wireless sensor network localization technology only relying on a single ranging means is reduced due to the increase in area of a monitoring region and the increase in noise. The technology is suitable for highly dynamic marine environments and may maintain good localization performance in a large range of monitoring region under high wave masking noise.

In order to achieve the above object, the present disclosure is achieved through the following technical scheme:

A wireless sensor network positioning method for marine search and rescue based on information fusion, including following steps:

S1, constructing an RSS ranging model and a TOA ranging model respectively in consideration of sea wave masking noise;

S2, fusing multi-source ranging information in the RSS ranging model and the TOA ranging model according to constraints, and constructing a hybrid ranging constrained least squares framework;

S3, introducing a buffer factor, and acquiring an initial position of a target position by using an algorithm for improving block pivot rotation, specifically including: by dividing the indexes in the variable to be found into two sets and defining a subset of corresponding variables, calculating a complementary basic solution thereof and determining whether the complementary basic solution is a feasible solution, if not, then updating the set, introducing a buffer factor in the update process; cyclically alternating the above-mentioned determination step and update step, and finally making each variable solution to be found be a feasible solution, that is, the initial solution of the target position; and

S4, deriving a linear re-optimization method based on the first-order expansion of the Taylor series, performing error correction in the initial solution obtained in S3, and obtaining a more accurate solution of the position.

The constructing an RSS ranging model and a TOA ranging model in step S1 specifically includes:

S11, if there are N anchor nodes in a network, expressing the position of the i^{th} anchor node at time t as $\mathbf{a}_i^t = [a_{i1}^t, a_{i2}^t]^T$, where T represents transposition; expressing the position of a target to be rescued at time t as $\mathbf{x}^t = [x_1^t, x_2^t]^T$; and receiving, by the anchor nodes, signal strength information from the target propagated through radio signals at each time, that is:

$$P_{ri}^t = \underbrace{P_s^t - PL(d_0)}_{P_0^t} - 10\alpha^t \log_{10} \frac{\|\mathbf{x}^t - \mathbf{a}_i^t\|}{d_0} + \gamma_i^t \quad (1a)$$

and constructing a ranging model that uses the signal strength information propagated through radio signals, that is, the RSS ranging model, where P_{ri}^t represents a transmitting power value of the target received by the i^{th} anchor node at time t ; d_0 represents a reference distance value, usually 1m; P_s^t represents a transmitting power of the target at time t ; $PL(d_0)$ represents a loss value of a transmitted signal strength at a relevant reference distance; α^t represents a path loss factor at time t ; $\|\mathbf{x}^t - \mathbf{a}_i^t\|$ represents a second-order norm; and γ_i^t represents sea wave masking noise of which the mean is zero and the variances are σ_i^t respectively and which satisfies Gaussian distribution in the RSS ranging model; and

S12, similarly, receiving, by the anchor nodes, time of arrival information from the target, which may be expressed as:

$$d_i^t = \|\mathbf{x}^t - \mathbf{a}_i^t\| + \eta_i^t, \quad (1b),$$

constructing a model that uses signal propagation time to range, that is, the TOA model, where η_i^t represents sea wave masking noise of which the mean is zero and the variances are δ_i^t respectively and which satisfies Gaussian distribution in the TOA ranging model.

The fusing multi-source ranging information in the RSS ranging model and the TOA ranging model, and constructing a hybrid ranging constrained least squares framework in step S2 specifically includes:

S21, performing term-shifting transformation according to the expression (1a) obtained in S11, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda_i^t \cdot 10^{\frac{\gamma_i^t}{10\alpha^t}} \quad (2),$$

where $\mu_i^t = 10^{\frac{P_{ri}^t}{10\alpha^t}}$; $\lambda^t = d_0 10^{\frac{P_0^t}{10\alpha^t}}$;

S22, linearly expanding the equation (2) obtained in S21, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda^t \cdot \left(1 + \frac{\ln 10}{10\alpha^t} \sigma\right) \quad (3);$$

S23, in consideration of constraints $\sigma_i^t \approx \sigma_i \approx \sigma$ and $\delta_i^t \approx \delta_i \approx \delta$, constructing the original localization problem as a hybrid ranging-based unconstrained least squares framework expression, that is:

$$\arg \min_{\mathbf{x}^t} \sum_{i=1}^N \left(\lambda^t - \mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 + \sum_{i=1}^N \left(d_i^t - \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 \quad (4);$$

S24, performing square expansion on the equation (4) obtained in S23, obtaining:

$$\begin{aligned} \arg \min_{\mathbf{x}^t} \sum_{i=1}^N & \left(\left\{ \lambda^t \right\}^2 - \left\{ \mu_i^t \right\}^2 \chi^t + 2 \left\{ \mu_i^t \right\}^2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\{ \mu_i^t \right\}^2 \left\| \mathbf{a}_i^t \right\|^2 \right)^2 \\ & + \sum_{i=1}^N \left(\left\{ d_i^t \right\}^2 - \chi^t + 2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\| \mathbf{a}_i^t \right\|^2 \right). \end{aligned} \quad (5); \text{ and}$$

S25, making $\boldsymbol{\theta}^t = [\chi^t, x_1^t, x_2^t]^T$ be a variable, where M represents the quantity to be found in the variable, and in conjunction with the constraint $\boldsymbol{\theta}^t \geq 0$, further constructing the original localization problem as a hybrid ranging constrained least squares (HM-CLS) framework, that is:

$$\arg \min_{\boldsymbol{\theta}^t \geq 0} \left\| \mathbf{A}^t \boldsymbol{\theta}^t - \mathbf{B}^t \right\|^2 \quad (6),$$

$$\text{where } \mathbf{A}^t = \begin{bmatrix} 2\{\mu_1^t\}^2 \{\mathbf{a}_1^t\}^T & -\{\mu_1^t\}^2 \\ \vdots & \vdots \\ 2\{\mu_N^t\}^2 \{\mathbf{a}_N^t\}^T & -\{\mu_N^t\}^2 \\ 2\{\mathbf{a}_1^t\}^T & -1 \\ \vdots & \vdots \\ 2\{\mathbf{a}_N^t\}^T & -1 \end{bmatrix}, \mathbf{B}^t = \begin{bmatrix} \{\mu_1^t\}^2 \left\| \mathbf{a}_1^t \right\|^2 - \{\lambda^t\}^2 \\ \vdots \\ \{\mu_N^t\}^2 \left\| \mathbf{a}_N^t \right\|^2 - \{\lambda^t\}^2 \\ \left\| \mathbf{a}_1^t \right\|^2 - \{d_1^t\}^2 \\ \vdots \\ \left\| \mathbf{a}_N^t \right\|^2 - \{d_N^t\}^2 \end{bmatrix}. \quad (7).$$

The introducing a buffer factor, and acquiring an initial solution of a target position by using an algorithm for improving block pivot rotation by cyclically alternating feasible solution indexes in step S3 specifically includes:

S31, dividing the indexes in the variable to be found into two sets, namely κ and $\mathcal{G}$, where $\kappa \cup \mathcal{G} = \{1, \dots, M\}$, $\kappa \cap \mathcal{G} = \emptyset$; in addition, defining ξ_κ , $\xi_{\mathcal{G}}$, Ψ_κ and $\Psi_{\mathcal{G}}$ as subsets of corresponding variables, and A_κ^t and $A_{\mathcal{G}}^t$ as sub-matrices of corresponding matrices A^t ;

S32, calculating a complementary basic solution $(\xi_\kappa, \Psi_{\mathcal{G}})$ according to equation (8) and equation (9), if satisfying the constraint $\xi_\kappa \geq 0$ and $\Psi_{\mathcal{G}} \geq 0$, taking the complementary basic solution as a feasible solution, otherwise, taking the complementary basic solution as an infeasible solution;

$$\xi_\kappa = \arg \min_{\xi_\kappa} \|A_\kappa^t \xi_\kappa - B^t\|^2 \quad (8)$$

$$\Psi_{\mathcal{G}} = (A_{\mathcal{G}}^t)^T (A_\kappa^t \xi_\kappa - B^t) \quad (9)$$

S33, when the complementary basic solution does not satisfy the constraint, defining a set Γ to satisfy:

$$\Gamma = \{j \in \kappa : \xi_j < 0\} \cup \{j \in \mathcal{G} : \Psi_j < 0\} \quad (10),$$

S34, for $j \in \Gamma$, taking the variable ξ_j as an infeasible solution; and further updating κ and $\mathcal{G}$ according to the rules of equation (11):

$$\begin{aligned} \kappa &= (\kappa - R) \cup (R \cap \mathcal{G}) \\ \mathcal{G} &= (\mathcal{G} - R) \cup (R \cap \kappa) \end{aligned} \quad (11),$$

where R is a non-empty subset and $R \subset \Gamma$;

S35, when the update rule falls into a loop or a corresponding solution cannot be found, finding a feasible solution using equation (12) as a candidate update rule, that is:

$$R = \{j : j = \max \{j \in \Gamma\}\} \quad (12);$$

S36, in the update process, introducing a buffer factor, if the infeasible solution increases, decreasing the buffer factor; if the buffer factor is 0, then finding a feasible solution using a candidate update rule and storing the feasible solution in β ; and

S37, performing cyclic updates according to S32 to S36 until each variable solution to be found is a feasible solution.

The deriving a linear re-optimization method based on a first-order expansion of Taylor series ,

performing error correction on the initial solution obtained in S3, and obtaining a more accurate solution of the position in step S4 specifically includes:

S41, further constructing the loss function according to the initial solution $\hat{\theta}_{\text{SCM}}^t$ obtained in S36, that is:

$$J = \left(\mathbf{A}^t \theta^t - \mathbf{B}^t \right)^T \mathbf{A}^t \theta^t - \mathbf{B}^t = \left(\theta^t - \hat{\theta}_{\text{SCM}}^t \right)^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \left(\theta^t - \hat{\theta}_{\text{SCM}}^t \right) \quad (13);$$

S42, using the first-order Taylor series expansion to expand $\theta^t - \hat{\theta}_{\text{SCM}}^t$ when $\theta_{1:2}^t$ approaches $\hat{\mathbf{x}}^t$, where $\theta_{1:2}^t$ represents the first two terms of the variable θ^t ; $\hat{\mathbf{x}}^t$ represents the final estimate, so the corresponding expression can become:

$$\theta^t - \hat{\theta}_{\text{SCM}}^t = \theta^t \Big|_{\theta_{1:2}^t = \hat{\mathbf{x}}^t} - \hat{\theta}_{\text{SCM}}^t + \frac{\partial \theta^t}{\partial (\theta_{1:2}^t)^T} \Big|_{\theta_{1:2}^t = \hat{\mathbf{x}}^t} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) = \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) \quad (14)$$

$$\Theta = \theta^t \Big|_{\theta_{1:2}^t = \hat{\mathbf{x}}^t} - \hat{\theta}_{\text{SCM}}^t = \begin{bmatrix} 0 \\ 0 \\ \|\hat{\mathbf{x}}^t\|^2 - \hat{\mathcal{X}}^t \end{bmatrix},$$

where

$$\mathfrak{I} = \frac{\partial \theta^t}{\partial (\theta_{1:2}^t)^T} \Big|_{\theta_{1:2}^t = \hat{\mathbf{x}}^t} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) = \begin{bmatrix} \mathbf{I}_2 \\ 2(\hat{\mathbf{x}}^t)^T \end{bmatrix}. \quad (15);$$

S43, in conjunction with the functions obtained in steps S41 and S42, further expressing the loss function as:

$$J = \left\{ \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) \right\}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \left\{ \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) \right\} \quad (16);$$

S44, through the expression obtained in S43, finding a partial derivative of $\theta_{1:2}^t$, obtaining:

$$\frac{\partial J}{\partial \theta_{1:2}^t} = 2 \mathfrak{I}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \mathfrak{I} (\theta_{1:2}^t - \hat{\mathbf{x}}^t) + 2 \mathfrak{I}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \Theta \quad (17); \text{ and}$$

S45, making the expression obtained in S44 be 0, obtaining an error, performing an error correction operation, obtaining:

$$\hat{\mathbf{x}}_{\text{corrected}}^t = \hat{\mathbf{x}}^t - \left\{ \mathfrak{I}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \mathfrak{I} \right\}^{-1} \mathfrak{I}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \Theta \quad (18).$$

The present disclosure has the following advantages compared with prior art: this method is suitable for highly dynamic marine environments, and can maintain good localization performance

in a large range of monitoring region and under high wave masking noise, solving the problem that the localization accuracy of a marine wireless sensor network localization technology only relying on a single ranging means is reduced due to the increase in monitoring area and the increase in noise.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 is a structural diagram of a marine search and rescue wireless sensor network system.

Figure 2 is a flow chart of a wireless sensor network positioning method for marine search and rescue based on information fusion.

Figure 3 is a pseudo code based on a localization algorithm for improving block pivot rotation of the present disclosure.

Figure 4(a) and Figure 4(b) show localization performance in different monitoring regions of the present disclosure.

Figure 5(a) and Figure 5(b) show localization performance under different noise of the present disclosure.

DETAILED DESCRIPTION

The present disclosure will be further elaborated by describing in detail a preferred specific implementation case in conjunction with the accompanying drawings below.

Figure 1 shows a structural block diagram of a marine search and rescue sensor network. When a ship is in distress, a target to be rescued (the larger diameter circle dot in Figure 1) carries a life jacket with a relevant node device, and a rescue helicopter goes to the relevant sea area to spread an anchor node with a GPS or Beidou signal that can obtain the position in real time (the smaller diameter circle dot in Figure 1). The anchor node and the node on the target to be rescued (target node) form a wireless sensor network through the Zigbee protocol, and then the problem of searching the target to be rescued becomes the problem of locating the network node. After obtaining the position of the target to be rescued, the anchor node transmits relevant information to a rescue ship and satellite, and the satellite transmits the relevant information to the relevant departments on land through the signal and the network to implement specific rescue plans.

Assuming that there are N anchor nodes in the network, the position of the i^{th} anchor node at time t can be expressed as $\mathbf{a}_i^t = [a_{i1}^t, a_{i2}^t]^T$. The position of the target to be rescued at time t is expressed as $\mathbf{x}^t = [x_1^t, x_2^t]^T$. The anchor nodes can receive Time of Arrival (TOA) and Received

Signal Strengths (RSS) information from the target propagated through radio signals at each time.

As shown in Figure 2, in order to locate the target, the present disclosure proposes a Lightweight Computational Localization Technology using Information Fusing (LCCT-IF), specifically including:

S1, constructing an RSS ranging model and a TOA ranging model in consideration of sea wave masking noise, respectively;

S2, fusing multi-source ranging information in the RSS ranging model and the TOA ranging model according to constraints, and constructing a hybrid ranging constrained least squares framework;

S3, introducing a buffer factor, and acquiring an initial solution of a target position by using an algorithm for improving block pivot rotation by cyclically alternating feasible solution indexes; and

S4, deriving a linear re-optimization method based the first-order Taylor series expansion, performing error correction on the initial solution obtained in S3, and obtaining a more accurate solution of the position.

In this implementation case, the step S1 specifically includes:

S11, expressing the received RSS information, that is, the RSS ranging model as:

$$P_{ri}^t = \underbrace{P_s^t - PL(d_0)}_{P_0^t} - 10\alpha^t \log_{10} \frac{\|\mathbf{x}^t - \mathbf{a}_i^t\|}{d_0} + \gamma_i^t, \quad (1a),$$

where P_{ri}^t represents a transmitting power value of the target received by the i^{th} anchor node at time t ; d_0 represents a reference distance value, usually 1m; P_s^t represents a transmitting power of the target at time t ; $PL(d_0)$ represents a loss value of a transmitted signal strength at a relevant reference distance; α^t represents a path loss factor at time t ; $\|\mathbf{x}^t - \mathbf{a}_i^t\|$ represents a second-order norm; and γ_i^t represents sea wave masking noise of which the mean is zero and the variances are σ_i^t respectively and which satisfies Gaussian distribution in the RSS ranging model; and

S12, similarly, receiving, by the anchor nodes, Time of Arrival (TOA) information from the target, that is, the TOA ranging model, which can be expressed as:

$$d_i^t = \|\mathbf{x}^t - \mathbf{a}_i^t\| + \eta_i^t, \quad (1b),$$

where η_i^t represents sea wave masking noise of which the mean is zero and the variances are δ_i^t respectively and which satisfies Gaussian distribution in the TOA ranging model.

The step S2 specifically includes:

S21, performing term-shifting transformation according to the expression (1a) obtained in S11, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda_i^t \cdot 10^{\frac{\gamma_i^t}{10\alpha^t}} \quad (2),$$

where $\mu_i^t = 10^{\frac{P_{ri}^t}{10\alpha^t}}$; $\lambda^t = d_0 10^{\frac{P_0^t}{10\alpha^t}}$;

S22, linearly expanding the equation (2) obtained in S21, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda^t \cdot \left(1 + \frac{\ln 10}{10\alpha^t} \sigma\right) \quad (3),$$

S23, in consideration of constraints $\sigma_i^t \approx \sigma_i \approx \sigma$ and $\delta_i^t \approx \delta_i \approx \delta$, constructing the original localization problem as a hybrid ranging-based unconstrained least squares framework expression, that is:

$$\arg \min_{\mathbf{x}^t} \sum_{i=1}^N \left(\lambda^t - \mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 + \sum_{i=1}^N \left(d_i^t - \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 \quad (4);$$

S24, performing square expansion on the equation (4) obtained in S23, obtaining:

$$\begin{aligned} \arg \min_{\mathbf{x}^t} \sum_{i=1}^N & \left(\left\{ \lambda^t \right\}^2 - \left\{ \mu_i^t \right\}^2 \chi^t + 2 \left\{ \mu_i^t \right\}^2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\{ \mu_i^t \right\}^2 \left\| \mathbf{a}_i^t \right\|^2 \right)^2 \\ & + \sum_{i=1}^N \left(\left\{ d_i^t \right\}^2 - \chi^t + 2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\| \mathbf{a}_i^t \right\|^2 \right) \end{aligned} \quad (5); \text{ and}$$

S25, making $\boldsymbol{\theta}^t = [x_1^t, x_2^t, \chi^t]^T$ be a variable, where M represents the quantity to be found in the variable, and in conjunction with the constraint $\boldsymbol{\theta}^t \geq 0$, further constructing the original localization problem as a hybrid ranging constrained least squares (HM-CLS) framework, that is:

$$\arg \min_{\boldsymbol{\theta}^t \geq 0} \left\| \mathbf{A}^t \boldsymbol{\theta}^t - \mathbf{B}^t \right\|^2 \quad (6)$$

$$\text{where } \mathbf{A}^t = \begin{bmatrix} 2\{\mu_1^t\}^2 \{\mathbf{a}_1^t\}^T & -\{\mu_1^t\}^2 \\ \vdots & \vdots \\ 2\{\mu_N^t\}^2 \{\mathbf{a}_N^t\}^T & -\{\mu_N^t\}^2 \\ 2\{\mathbf{a}_1^t\}^T & -1 \\ \vdots & \vdots \\ 2\{\mathbf{a}_N^t\}^T & -1 \end{bmatrix}, \mathbf{B}^t = \begin{bmatrix} \{\mu_1^t\}^2 \|\mathbf{a}_1^t\|^2 - \{\lambda^t\}^2 \\ \vdots \\ \{\mu_N^t\}^2 \|\mathbf{a}_N^t\|^2 - \{\lambda^t\}^2 \\ \|\mathbf{a}_1^t\|^2 - \{d_1^t\}^2 \\ \vdots \\ \|\mathbf{a}_N^t\|^2 - \{d_N^t\}^2 \end{bmatrix} \quad (7).$$

The step S3 specifically includes:

S31, dividing the indexes in the variable to be found into two sets, namely κ and $\mathcal{G}$, where $\kappa \cup \mathcal{G} = \{1, \dots, M\}$, $\kappa \cap \mathcal{G} = \emptyset$; in addition, defining ξ_κ , $\xi_{\mathcal{G}}$, Ψ_κ and $\Psi_{\mathcal{G}}$ as subsets of corresponding variables, and $\mathbf{A}_\kappa^t$ and $\mathbf{A}_{\mathcal{G}}^t$ as sub-matrices of corresponding matrices $\mathbf{A}^t$;

S32, calculating a complementary basic solution $(\xi_\kappa, \Psi_{\mathcal{G}})$ according to equation (8) and equation (9), if satisfying the constraint $\xi_\kappa \geq 0$ and $\Psi_{\mathcal{G}} \geq 0$, taking the complementary basic solution as a feasible solution, otherwise, taking the complementary basic solution as an infeasible solution.

$$\xi_\kappa = \arg \min_{\xi_\kappa} \|\mathbf{A}_\kappa^t \xi_\kappa - \mathbf{B}^t\|^2 \quad (8)$$

$$\Psi_{\mathcal{G}} = (\mathbf{A}_{\mathcal{G}}^t)^T (\mathbf{A}_\kappa^t \xi_\kappa - \mathbf{B}^t) \quad (9);$$

S33, when the complementary basic solution does not satisfy the constraint, defining a set Γ to satisfy:

$$\Gamma = \{j \in \kappa : \xi_j < 0\} \cup \{j \in \mathcal{G} : \Psi_j < 0\} \quad (10);$$

S34, for $j \in \Gamma$, taking the variable ξ_j as an infeasible solution, and further updating κ and $\mathcal{G}$ according to the rules of equation (11):

$$\begin{aligned} \kappa &= (\kappa - R) \cup (R \cap \mathcal{G}) \\ \mathcal{G} &= (\mathcal{G} - R) \cup (R \cap \kappa) \end{aligned} \quad (11),$$

where R is a non-empty subset and $R \subset \Gamma$;

S35, when the update rule falls into a loop or a corresponding solution cannot be found,

finding a feasible solution using equation (12) as a candidate update rule, that is:

$$R = \{j : j = \max\{j \in \Gamma\}\} \quad (12);$$

S36, in the update process, introducing a buffer factor φ , if the infeasible solution increases, decreasing buffer factor, if the buffer factor is 0, finding a feasible solution using a candidate update rule and store the feasible solution in β ; and

S37, performing cyclic updates according to S32 to S36 until each variable solution to be found is a feasible solution.

The detailed pseudo code based on the algorithm for improving block pivot rotation is shown in Figure 3.

The step S4 specifically includes:

S41, further constructing the loss function according to the initial solution $\hat{\theta}_{\text{SCM}}^t$ obtained in S36, that is:

$$J = (A^t \theta^t - B^t)^T A^t \theta^t - B^t = (\theta^t - \hat{\theta}_{\text{SCM}}^t)^T (A^t)^T A^t (\theta^t - \hat{\theta}_{\text{SCM}}^t). \quad (13);$$

S42, using the first-order expansion of Taylor series to expand $\theta^t - \hat{\theta}_{\text{SCM}}^t$ when $\theta_{1:2}^t$ approaches $\hat{x}^t$, where $\theta_{1:2}^t$ represents the first two terms of the variable θ^t ; $\hat{x}^t$ represents the final estimate, so the corresponding expression can become:

$$\theta^t - \hat{\theta}_{\text{SCM}}^t = \theta^t \Big|_{\theta_{1:2}^t = \hat{x}^t} - \hat{\theta}_{\text{SCM}}^t + \frac{\partial \theta^t}{\partial (\theta_{1:2}^t)^T} \Big|_{\theta_{1:2}^t = \hat{x}^t} (\theta_{1:2}^t - \hat{x}^t) = \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{x}^t) \quad (14)$$

$$\text{where } \Theta = \theta^t |_{\theta_{1:2}^t = \hat{x}^t} - \hat{\theta}_{\text{SCM}}^t = \begin{bmatrix} 0 \\ 0 \\ \|\hat{x}^t\|^2 - \hat{x}^t \end{bmatrix}$$

$$\mathfrak{I} = \frac{\partial \theta^t}{\partial (\theta_{1:2}^t)^T} |_{\theta_{1:2}^t = \hat{x}^t} (\theta_{1:2}^t - \hat{x}^t) = \begin{bmatrix} I_2 \\ 2(\hat{x}^t)^T \end{bmatrix} \quad (15);$$

S43, in conjunction with the functions obtained in S41 and S42, further expressing the loss function as:

$$J = \left\{ \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{x}^t) \right\}^T (A^t)^T A^t \left\{ \Theta + \mathfrak{I} (\theta_{1:2}^t - \hat{x}^t) \right\} \quad (16);$$

S44, through the expression obtained in S43, finding a partial derivative of $\theta_{1:2}^t$, obtaining:

$$\frac{\partial J}{\partial \theta_{1:2}^t} = 2\mathfrak{Z}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \mathfrak{Z} \left(\theta_{1:2}^t - \hat{\mathbf{x}}^t \right) + 2\mathfrak{Z}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \Theta \quad (17); \text{ and}$$

S45, making the expression obtained in S44 be 0, obtaining an error, performing an error correction operation, obtaining:

$$\hat{\mathbf{x}}_{\text{corrected}}^t = \hat{\mathbf{x}}^t - \left\{ \mathfrak{Z}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \mathfrak{Z} \right\}^{-1} \mathfrak{Z}^T \left(\mathbf{A}^t \right)^T \mathbf{A}^t \Theta \quad (18).$$

In order to verify the effectiveness of the LCCT-IF provided by the present disclosure in localization when a shipwreck occurs, a simulation experiment is conducted in Matlab R2021b, and the ocean high dynamics is simulated using a random walk model, so that the positions of all targets and anchor nodes change at each time. By comparing different information fusion localization algorithms, such as weighted least squares (WLS), square ranging weighted least squares (SRWLS), linear least squares (LLS), and semi-definite programming (SDP), taking the root mean square error as an evaluation criterion, that is, equation (19), and the simulation experiment is conducted under different conditions.

$$RMSE = \sqrt{\frac{1}{t_{\max}} \sum_{t=1}^{t_{\max}} \left\| \hat{\mathbf{x}}^t - \mathbf{x}^t \right\|^2} \quad (19)$$

where $\mathbf{x}^t$ represents the true position; $\hat{\mathbf{x}}^t$ represents the estimated position; $t_{\max}$ represents the total time, which is set to 1000 s in the simulation.

Figure 4 shows the localization performance in different monitoring regions. Affected by sea wind flow, etc., the falling target will be dynamically affected as time goes, so the area of the monitoring region will also dynamically change. The side length of the monitoring region is set as a variable, and other related parameters are set as: $\sigma_i^2 = 5 \text{ dB}$, $\delta_i^2 = 5 \text{ m}$, $\alpha^t = 3.5$, $P_0^t = -55 \text{ dBm}$, $N = 8$. Figure 4(a) shows localization errors under different region side lengths. It can be seen from the figure that the localization errors of WLS, SRWLS and SDP increase as the area of the monitoring region increases. However, the LLS and the LCCT-IF proposed in the present disclosure have a certain degree of robustness to the change in the monitoring region, and the localization errors thereof are maintained at a relatively stable level. The LCCT-IF of the present disclosure has

better localization accuracy than the LLS. It can be seen from Figure 4(b) that the LCCT-IF can maintain an error within 5m with a probability of 95% in different monitoring regions, which is better than the LLS with the best perform among other algorithms (maintaining an error of 7m when achieving the same probability of 95%).

Figure 5 shows the localization performance under different noise. Since the maritime environment is complex and changeable, the channel conditions are relatively complex. To this end, the localization accuracy under different noise conditions needs to be verified. The simulation is carried out in a square monitoring region with a side length of 100m. The relevant parameters are specifically set as follows: $N = 8$, $\alpha^t = 3.5$, $P_0^t = -55$ dBm. It can be seen from Figure 5(a) that the localization error increases with the increase of noise. The LCCT-IF proposed by the present disclosure has better performance than other methods, and localization error thereof can always be maintained within 3m. In addition, it can be seen from Figure 5(b) that the algorithm proposed by the present disclosure can make the probability of errors less than 1.89m, 3.32m, 4.16m and 5.06m reach 95% under different noise conditions, while for other methods when achieving the same probability, each of the errors thereof exceeds that of the LCCT-IF.

Although the content of the present disclosure has been described in detail through the above preferred embodiment, it should be recognized that the above description should not be considered as limiting the present disclosure. Various modifications and substitutions to the present disclosure will be apparent to those skilled in the art after reading the above content. Therefore, the protection scope of the present disclosure should be defined by the appended claims.

1. A lightweight computational localization technology using information fusing, comprising following steps:

S1, constructing an RSS ranging model and a TOA ranging model in consideration of sea wave masking noise, respectively;

S2, fusing multi-source ranging information in the RSS ranging model and the TOA ranging model according to constraints, and constructing a hybrid ranging constrained least squares framework;

S3, introducing a buffer factor, and acquiring an initial position of a target position by using an algorithm for improving block pivot rotation, specifically including: by dividing the indexes in the variable to be found into two sets and defining a subset of corresponding variables, calculating a complementary basic solution thereof and determining whether the complementary basic solution is a feasible solution, if not, then updating the set, introducing a buffer factor in the update process; cyclically alternating the above-mentioned judgment step and update step, and finally making each variable solution to be found be a feasible solution, that is, the initial solution of the target position; and

S4, performing error correction on the initial solution described in S3, constructing a loss function first, then performing linear re-optimization based on the first-order expansion of Taylor series, and obtaining a more accurate error-corrected solution of the position through error correction.

2. The lightweight computational localization technology using information fusing according to claim 1, wherein the constructing an RSS ranging model and a TOA ranging model in consideration of sea wave masking noise respectively in step S1 specifically comprises:

S11, if there are N anchor nodes in a network, expressing the position of the i^{th} anchor node at time t as $\mathbf{a}_i^t = [a_{i1}^t, a_{i2}^t]^T$, and expressing the position of a target to be rescued at time t as $\mathbf{x}^t = [x_1^t, x_2^t]^T$; receiving, by the anchor nodes, signal strength information from the target propagated through radio signals at each time, forming an RSS ranging model that uses the signal strength information propagated through radio signals to range, that is:

$$P_{ri}^t = \underbrace{P_s^t - PL(d_0)}_{P_0^t} - 10\alpha^t \log_{10} \frac{\|\mathbf{x}^t - \mathbf{a}_i^t\|}{d_0} + \gamma_i^t \quad (1a),$$

wherein P_{ri}^t represents a transmitting power value of the target received by the i^{th} anchor node at time t ; d_0 represents a reference distance value, usually 1m; P_s^t represents a transmitting power of the target at time t ; $PL(d_0)$ represents a loss value of a transmitted signal strength at a relevant reference distance; α^t represents a path loss factor at time t ; $\|\mathbf{x}^t - \mathbf{a}_i^t\|$ represents a second-order norm; and γ_i^t represents sea wave masking noise of which the mean is zero and the variances are σ_i^t respectively and which satisfies Gaussian distribution in the RSS ranging model; and

S12, similarly, receiving, by the anchor nodes, time of arrival information from the target, and constructing a TOA ranging model that uses signal propagation time to range, which is expressed as:

$$d_i^t = \|\mathbf{x}^t - \mathbf{a}_i^t\| + \eta_i^t, \quad (1b),$$

wherein η_i^t represents sea wave masking noise of which the mean is zero and the variances are δ_i^t respectively and which satisfies Gaussian distribution in the TOA ranging model.

3. The lightweight computational localization technology using information fusing according to claim 2, wherein the fusing ranging information in the RSS ranging model and the TOA ranging model, and constructing a hybrid ranging constrained least squares framework in conjunction with constraints in step S2 specifically comprises:

S21, performing term-shifting transformation according to the expression (1a) obtained in S11, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda_i^t \cdot 10^{\frac{\gamma_i^t}{10\alpha^t}} \quad (2)$$

$$\text{wherein } \mu_i^t = 10^{\frac{P_{ri}^t}{10\alpha^t}}; \quad \lambda^t = d_0 10^{\frac{P_0^t}{10\alpha^t}};$$

S22, linearly expanding the equation (2) obtained in S21, obtaining:

$$\mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| = \lambda^t \cdot \left(1 + \frac{\ln 10}{10\alpha^t} \sigma\right) \quad (3);$$

S23, in consideration of constraints $\sigma_i^t \approx \sigma_i \approx \sigma$ and $\delta_i^t \approx \delta_i \approx \delta$, and in conjunction with equation (1b), constructing an original localization problem as a hybrid ranging-based unconstrained least squares framework expression, that is:

$$\arg \min_{\mathbf{x}^t} \sum_{i=1}^N \left(\lambda^t - \mu_i^t \cdot \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 + \sum_{i=1}^N \left(d_i^t - \|\mathbf{x}^t - \mathbf{a}_i^t\| \right)^2 \quad (4);$$

S24, performing square expansion on the equation (4) obtained in S23, obtaining:

$$\begin{aligned} \arg \min_{\mathbf{x}^t} \sum_{i=1}^N & \left(\left\{ \lambda^t \right\}^2 - \left\{ \mu_i^t \right\}^2 \chi^t + 2 \left\{ \mu_i^t \right\}^2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\{ \mu_i^t \right\}^2 \left\| \mathbf{a}_i^t \right\|^2 \right)^2 \\ & + \sum_{i=1}^N \left(\left\{ d_i^t \right\}^2 - \chi^t + 2 \left\{ \mathbf{a}_i^t \right\}^T \mathbf{x}^t - \left\| \mathbf{a}_i^t \right\|^2 \right) \end{aligned} \quad (5); \text{ and}$$

S25, making $\boldsymbol{\theta}^t = [\chi_1^t, \chi_2^t, \chi^t]^T$ be a variable, wherein M represents the quantity to be found in the variable, and in conjunction with the constraint $\boldsymbol{\theta}^t \geq 0$, further constructing the original localization problem as a hybrid ranging constrained least squares (HM-CLS) framework, that is:

$$\arg \min_{\boldsymbol{\theta}^t \geq 0} \left\| \mathbf{A}^t \boldsymbol{\theta}^t - \mathbf{B}^t \right\|^2. \quad (6),$$

wherein

$$\mathbf{A}^t = \begin{bmatrix} 2\left\{ \mu_1^t \right\}^2 \left\{ \mathbf{a}_1^t \right\}^T & -\left\{ \mu_1^t \right\}^2 \\ \vdots & \vdots \\ 2\left\{ \mu_N^t \right\}^2 \left\{ \mathbf{a}_N^t \right\}^T & -\left\{ \mu_N^t \right\}^2 \\ 2\left\{ \mathbf{a}_1^t \right\}^T & -1 \\ \vdots & \vdots \\ 2\left\{ \mathbf{a}_N^t \right\}^T & -1 \end{bmatrix}, \mathbf{B}^t = \begin{bmatrix} \left\{ \mu_1^t \right\}^2 \left\| \mathbf{a}_1^t \right\|^2 - \left\{ \lambda^t \right\}^2 \\ \vdots \\ \left\{ \mu_N^t \right\}^2 \left\| \mathbf{a}_N^t \right\|^2 - \left\{ \lambda^t \right\}^2 \\ \left\| \mathbf{a}_1^t \right\|^2 - \left\{ d_1^t \right\}^2 \\ \vdots \\ \left\| \mathbf{a}_N^t \right\|^2 - \left\{ d_N^t \right\}^2 \end{bmatrix} \quad (7), \text{ and}$$

wherein $\mathbf{A}^t$ and $\mathbf{B}^t$ are matrix parameter values of the hybrid ranging constrained least squares (HM-CLS) framework.

4. The lightweight computational localization technology using information fusing according to claim 3, wherein the introducing a buffer factor, and acquiring an initial solution of a target position by using an algorithm for improving block pivot rotation in step S3 specifically comprises:

S31, dividing the M indexes in the variable to be found in S25 into two sets, namely κ and $\mathcal{G}$, where $\kappa \cup \mathcal{G} = \{1, \dots, M\}$, $\kappa \cap \mathcal{G} = \emptyset$; in addition, defining ξ_κ , $\xi_{\mathcal{G}}$, Ψ_κ and $\Psi_{\mathcal{G}}$ as subsets of corresponding variables, and $\mathbf{A}_\kappa^t$ and $\mathbf{A}_{\mathcal{G}}^t$ as sub-matrices of corresponding matrices;

S32, calculating a complementary basic solution (ξ_κ, Ψ_g) according to equation (8) and equation (9), if satisfying the constraint $\xi_\kappa \geq 0$ and $\Psi_g \geq 0$, taking the complementary basic solution as a feasible solution, otherwise, taking the complementary basic solution as an infeasible solution;

$$\xi_\kappa = \arg \min_{\xi_\kappa} \|A_\kappa^t \xi_\kappa - B^t\|^2 \quad (8)$$

$$\Psi_g = (A_g^t)^T (A_\kappa^t \xi_\kappa - B^t) \quad (9);$$

S33, when the complementary basic solution does not satisfy the constraint, defining a set Γ to satisfy:

$$\Gamma = \{j \in \kappa : \xi_j < 0\} \cup \{j \in g : \Psi_j < 0\} \quad (10);$$

S34, for $j \in \Gamma$, taking the variable ξ_j as an infeasible solution; and further updating κ and g according to the rules of equation (11):

$$\begin{aligned} \kappa &= (\kappa - R) \cup (R \cap g) \\ g &= (g - R) \cup (R \cap \kappa) \end{aligned} \quad (11),$$

wherein R is a non-empty subset and $R \subset \Gamma$;

S35, when the update rule falls into a loop or a corresponding solution cannot be found, finding a feasible solution using equation (12) as a candidate update rule, that is:

$$R = \{j : j = \max\{j \in \Gamma\}\} \quad (12);$$

S36, in the update process, introducing a buffer factor, if the infeasible solution increases, decreasing the buffer factor; if the buffer factor is 0, finding a feasible solution using the candidate update rule and storing the feasible solution in β ; and

S37, performing cyclic updates according to S32 to S36 until each variable solution to be found is a feasible solution, that is, the initial solution of the target position.

5. The lightweight computational localization technology using information fusing according to claim 4, wherein the deriving a linear re-optimization method based on a first-order Taylor series expansion, performing error correction on the initial solution obtained in S36, and obtaining a more accurate solution of the position in step S4 includes:

S41, further constructing the loss function according to the initial solution $\hat{\theta}_{\text{SCM}}^t$ obtained in S36, that is:

$$J = (\mathbf{A}^t \boldsymbol{\theta}^t - \mathbf{B}^t)^T \mathbf{A}^t \boldsymbol{\theta}^t - \mathbf{B}^t = (\boldsymbol{\theta}^t - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t)^T (\mathbf{A}^t)^T \mathbf{A}^t (\boldsymbol{\theta}^t - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t) \quad (13),$$

S42, using the first-order Taylor series expansion to expand $\boldsymbol{\theta}^t - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t$ when $\boldsymbol{\theta}_{1:2}^t$ approaches $\hat{\mathbf{x}}^t$, where $\boldsymbol{\theta}_{1:2}^t$ represents the first two terms of the variable $\boldsymbol{\theta}^t$; $\hat{\mathbf{x}}^t$ represents the final estimate, so the corresponding expression can become:

$$\boldsymbol{\theta}^t - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t = \boldsymbol{\theta}^t \Big|_{\boldsymbol{\theta}_{1:2}^t = \hat{\mathbf{x}}^t} - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t + \frac{\partial \boldsymbol{\theta}^t}{\partial (\boldsymbol{\theta}_{1:2}^t)^T} \Big|_{\boldsymbol{\theta}_{1:2}^t = \hat{\mathbf{x}}^t} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t) = \boldsymbol{\Theta} + \boldsymbol{\Im} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t). \quad (14),$$

wherein

$$\begin{aligned} \boldsymbol{\theta} = \boldsymbol{\theta}^t |_{\boldsymbol{\theta}_{1:2}^t = \hat{\mathbf{x}}^t} - \hat{\boldsymbol{\theta}}_{\text{SCM}}^t &= \begin{bmatrix} 0 \\ 0 \\ \|\hat{\mathbf{x}}^t\|^2 - \hat{\mathbf{x}}^t \end{bmatrix} \\ \boldsymbol{\Im} = \frac{\partial \boldsymbol{\theta}^t}{\partial (\boldsymbol{\theta}_{1:2}^t)^T} \Big|_{\boldsymbol{\theta}_{1:2}^t = \hat{\mathbf{x}}^t} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t) &= \begin{bmatrix} I_2 \\ 2(\hat{\mathbf{x}}^t)^T \end{bmatrix} \end{aligned} \quad (15);$$

S43, in conjunction with the functions obtained in steps S41 and S42, further expressing the loss function as:

$$J = \left\{ \boldsymbol{\Theta} + \boldsymbol{\Im} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t) \right\}^T (\mathbf{A}^t)^T \mathbf{A}^t \left\{ \boldsymbol{\Theta} + \boldsymbol{\Im} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t) \right\} \quad (16);$$

S44, through the expression obtained in S43, finding a partial derivative of $\boldsymbol{\theta}_{1:2}^t$, obtaining:

$$\frac{\partial J}{\partial \boldsymbol{\theta}_{1:2}^t} = 2 \boldsymbol{\Im}^T (\mathbf{A}^t)^T \mathbf{A}^t \boldsymbol{\Im} (\boldsymbol{\theta}_{1:2}^t - \hat{\mathbf{x}}^t) + 2 \boldsymbol{\Im}^T (\mathbf{A}^t)^T \mathbf{A}^t \boldsymbol{\Theta} \quad (17); \text{ and}$$

S45, making the expression obtained in S44 be 0, obtaining an error, performing an error correction operation, obtaining:

$$\hat{\mathbf{x}}_{\text{corrected}}^t = \hat{\mathbf{x}}^t - \left\{ \boldsymbol{\Im}^T (\mathbf{A}^t)^T \mathbf{A}^t \boldsymbol{\Im} \right\}^{-1} \boldsymbol{\Im}^T (\mathbf{A}^t)^T \mathbf{A}^t \boldsymbol{\Theta} \quad (18),$$

that is, $\hat{\mathbf{x}}_{\text{corrected}}^t$ is an error-corrected solution.