AOA Positioning and Path Optimization of UAV Swarm Based on A-optimality

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ABSTRACT In this paper, an angles of arrival (AOA) localization algorithm based on A-optimality criterion is proposed to solve the problem of unmanned aerial vehicle (UAV) Swarm locating various motion states targets. Firstly, a multi-sites AOA positioning model and a model of error variance changing with the received signal-to-noise ratio are established. Then, A-optimality criterion under this model is derived theoretically, and the optimal spatial configuration of UAV Swarm is analyzed by FIM. Secondly, the target is located by ML algorithm, and the change of flight angle and flight distance of UAV Swarm is analyzed with the minimum value of CRLB matrix trace as the objective function. At last, real-time path optimization is carried out on the flight path of UAV Swarm at the next moment. Simulation results show that path optimization is able to effectively improve the positioning accuracy of UAVs in various motion states.

INDEX TERMS angles of arrival (AOA) positioning; unmanned aerial vehicle (UAV) Swarm; A-optimality; path optimization

I. INTRODUCTION

In recent years, with the maturity and development of UAV technology theory as well as others related technologies, the technology of locating and tracking targets in the air by UAV Swarm has become more and more popular. American scholars John Aquila and David Longfield once pointed out that "Swarm warfare" would become the fourth battle in human history after "melee", "assembly warfare" and "mobile warfare" [1-2]. Generally speaking, "Swarm warfare" using UAV Swarm will play an increasingly important role in the future battle for air superiority. UAV Swarm refers to a considerable number of single/multi-functional unmanned aerial platforms, which are based on the independent ability of platform individuals, characterized by distribution and integration, and pursuing the emergence of higher-level intelligence. Intelligent individuals can cooperate and coordinate with each other to complete complex tasks together [3]. The arrival angle, arrival time, arrival frequency and other information of the aerial measured target can be extracted by the array sensor carried by UAV Swarm, which can achieve high-precision positioning in a short time, and the station arrangement mode is flexible with low manufacturing cost. Therefore, this technology is widely used.

Usually, the positioning system is determined by the observed quantity. At present, the common positioning systems are mainly AOA [4], RSS [5], TOA [6], TDOA [7-8] and FDOA [9-10]. Among them, the angle of arrival positioning method is also called lateral cross positioning method, which mainly uses multiple sensors to receive the azimuth information in the feedback information radiated by the measured target. The azimuth information is generally expressed by the angle of the signal received by the receiver relative to the unified reference line of each sensor, so as to obtain the connecting line between each sensor and the measured target, and the intersection of many connecting lines forms the approximate existing position of the target. Finally, the estimated position of the measured target is calculated. As the principle involved in AOA positioning method is simple, it usually requires at least two sensors to achieve accurate positioning, and the
synchronization between sensors is low, so this positioning system is widely used. Literature [11] perfectly solves the problem of positioning vulgar electromagnetic targets by mobile single station by establishing AOA two-dimensional physical positioning model in mobile single station positioning. Reference [12] proves that AOA positioning method is more accurate in multi observation station cooperative positioning. Reference [13] describes the application of AOA positioning for three-dimensional targets indoors. Reference [14] has solved the problem of the optimal position of the sensor in the AOA positioning method. Reference [15] shows that in AOA positioning system, the positioning accuracy obtained by using moving sensors is higher than that obtained by static sensors.

Location solution, whose essence is in fact the estimation of deterministic parameters, can mainly use least square estimation (LS) and maximum likelihood estimation (ML). The least square estimation needs to be given the mean value and covariance of observation errors, while the maximum likelihood estimation makes the best use of prior information, and its performance can approach Cramer-Rao lower bound. Search method, iterative method and analytical method are often used in the application of solution methods. The common search algorithms are genetic algorithm [16], particle swarm optimization [17-18], grid search method [19] and differential evolution algorithm [20-21]. The algorithm is essentially a maximum likelihood estimation method, which mainly traverses all possible values of the reference quantity to be estimated and calculates the corresponding objective function. When the objective function is the search value satisfying certain conditions, it is considered as the estimated value of the reference quantity to be estimated. The feature of this method is that its positioning error can approach Cramer-Rao lower bound well even when the observation noise is very high, but the disadvantage is that the computation will increase sharply with the dimension of the reference quantity to be estimated. The iterative method mainly uses the correction quantity estimated by the least squares to carry out Taylor expansion on the parameter to be estimated, and then obtains the estimated value of the parameter to be estimated by repeated iteration for several times. Its basic solution methods are Newton-Raphson iterative method [22] and Gauss-Newton iterative method [23], etc. Both iterative methods can solve the problem of nonlinear estimation. When the observation noise is Gaussian noise and small, its performance can approach Cramer-Rao lower bound, while its disadvantage is that it requires higher initial value, otherwise it is easy to diverge. Its analytical methods mainly include spherical intersection (SX) method [24] and spherical interpolation (SI) method [25]. The basic idea is to establish the nonlinear observation equation first, and then deduce the analytical formula of the target parameters to be measured approximately pseudo-linearly. Compared with the search method, the analytical method has less computation; Compared with iterative method, analytical method does not need initial value estimation, and there is no divergence problem. Moreover, when certain conditions are met, the positioning error of analytical method can effectively approach Cramer-Rao lower bound, so the application and research of analytical method are also extensive. In passive localization, the layout of sensors has a vital impact on the final positioning accuracy, and a good layout can effectively improve the positioning accuracy. Therefore, when the number of sensors and the positioning system involved are determined, real-time planning of the track of sensors according to the real-time motion state of the target can improve the final positioning accuracy. Literature [26-27] deduced the corresponding optimal configuration for different positioning systems according to Fisher information matrix. Generally, positioning accuracy is used to evaluate the positioning performance of sensors under different positioning algorithms and different positioning configurations. The general evaluation indexes include Cramer-Rao lower bound (CRLB), Geometric Dilution of Precision (GDOP), Cumulative Distribution Function (CDF), Relative Precision Error (PRF), etc.

The difference from the recent research on AOA positioning is that this paper uses the mobile distributed UAV swarm for AOA positioning, divides the motion state of the measured target in space into many types according to the actual situation, and makes a comparative analysis of positioning one by one. In the construction of positioning model, in addition to the existing AOA positioning model, the model of error variance varying with the received signal-to-noise ratio is also constructed. In the process of positioning solution, considering the positioning error and the real-time planning of UAV track, ML algorithm is adopted, combined with an optimization [28] with high optimization accuracy, and the minimum value of CRLB matrix trace is taken as the objective function. The flight path of UAV swarm is optimized in real time, so as to improve the positioning accuracy and positioning stability.

II. POSITIONING PRINCIPLE AND MODELING

A. PRINCIPLE OF AOA POSITIONING MEASUREMENT

The principle of dual-UAV AOA positioning and measurement is shown in Fig. 1. It can be seen that when two UAVs receive the azimuth information of the measured target, they first connect the azimuth between their own position and the measured target position, and then calculate the intersection of the two connections by the position calculation method, which is the approximate estimated position of the measured target.
B. AOA LOCATION MEASUREMENT MODEL BASED ON MULTI-STATION.

In the actual positioning operation process, in order to improve the positioning accuracy and reliability, multiple UAVs are often used for aerial positioning of the measured target. The two-dimensional configuration of N UAVs is shown in Fig. 2. It is assumed that the coordinate position of the i UAV in two-dimensional space is: 
\[ X_i(n) = [x_i(n), y_i(n)]^T \]
and the two-dimensional position of the measured target is: 
\[ X_t = [x_t, y_t]^T \]
where \( l_i \) is the distance between the i UAV and the measured target, and the included angle between every two adjacent UAVs is: \( \theta_{ij} \in [0, \pi] \). Then the AOA positioning estimation equation of UAV Swarm for the measured target can be written as: 
\[ \hat{\theta}_i = \theta_i(X_i) + e_i \]
where \( e_i \) is the measurement error, \( e_i \sim N(0, \sigma_i^2) \) and \( \sigma_i^2 \) is the variance of zero mean Gaussian white noise. Therefore, the angle \( \theta_i(X_i) \) between the UAV and the target can be expressed as:
\[ \theta_i(X_i) = \arctan 2(x_i - x_t, y_i - y_t) \]  
(1)

The measured value set of N UAVs with sensors can be expressed as [29]:
\[ \hat{\theta}_i = \theta_i(X_i) + e \]
(2)

in which: \( \theta_i(X_i) = [\theta_1(x_i), \theta_2(x_i), \ldots, \theta_N(x_i)]^T \)
\( e = [e_1, e_2, \ldots, e_N]^T \) and here, it is assumed that the measurement errors of each UAV are independent, and the error covariance is \( R = \sigma^2 N I_N \)

C. RANGE-DEPENDENT NOISE MODEL

For range-dependent noise, when the bandwidth of the signal received by UAV is constant, the final measurement error has a great relationship with the signal-to-noise ratio of the received signal. Assuming that the signal frequency and radiation power are constant, the distance between UAV and target determines the value of signal-to-noise ratio. Specifically, the variance of UAV positioning error is inversely proportional to the signal-to-noise ratio [30], from which the relationship between the positioning error of the i UAV and the distance between target and UAV can be expressed as:

\[ \sigma^2_i(r) = \begin{cases} \frac{\lambda}{\text{SNR}_0} \cdot \frac{l_i^2}{l_0^2} & l_i > l_0 \\ \frac{\lambda}{\text{SNR}_0} & l_i \leq l_0 \end{cases} \]

(3)

where, \( l_0 \) is the lower limit distance corresponding to the minimum positioning error variance of UAV, \( \text{SNR}_0 \) is the minimum signal-to-noise ratio, and \( \lambda \) is the fixed path loss index. It can be seen from this formula that when \( l_i > l_0 \)
the positioning error \( \sigma^2_i(r) \) is proportional to the square \( l_i^2 \) of the distance between the i UAV and the measured target, and when \( l_i \leq l_0 \), the positioning error \( \sigma^2_i(r) \) has...
nothing to do with the square $l_i^2$ of the distance between the $i$ UAV and the measured target.

### III. EVALUATION AND ANALYSIS OF POSITIONING ACCURACY

When the positioning system is determined, the evaluation and analysis of positioning accuracy is one of the most important tasks. Generally, Cramer-Rao lower bound (CRLB) can be used as a measure to evaluate the positioning performance. Cramer-Rao lower bound represents the minimum error covariance matrix that unbiased estimators can achieve, which has nothing to do with the specific positioning algorithm, but only reflects the attributes of the estimation problem itself. Specifically, the corresponding CRLB can be obtained by inverting the Fisher information matrix (FIM) of parameter estimation.

In this AOA positioning model, for the unbiased estimator $\hat{X}$ of the measured target $X$, its CRLB is:

$$J^{-1} = \text{CRLB} \left( X \right) \leq E[(X - \hat{X})(X - \hat{X})^T]$$  \hspace{1cm} (4)

where $J$ is Fisher information matrix. For the measurement estimate $\hat{\theta}_i = \theta(X) + e_i$ of the measured target, its probability density function $f_{\theta \mid X}$ can be expressed as:

$$f_{\theta \mid X} = \frac{1}{(2\pi)^{\frac{N}{2}}} \exp\left[-\frac{1}{2} \left(\hat{\theta} - \theta(X)\right)^T R^{-1}(\hat{\theta} - \theta(X))\right]$$  \hspace{1cm} (5)

The elements in FIM of measurement estimator $\hat{\theta}_i$ of the measured target can be expressed as:

$$J_{i,j} = E \left[ \frac{\partial}{\partial X_i} \ln(f_{\theta \mid X}) \frac{\partial}{\partial X_j} \ln(f_{\theta \mid X}) \right]$$  \hspace{1cm} (6)

Through the above formula, the FIM expression under AOA positioning method with distance-dependent noise can be further derived:

$$J_{i,j}(\hat{\theta}) = J_{i,j}(\theta(X)) + J_{i,j}(e_i)$$  \hspace{1cm} (7)

$J_{i,j}(\theta(X))$ is the FIM element of measurement and estimation, which can be expressed as:

$$J_{i,j}(\theta(X)) = \frac{1}{\sigma^2(X)} \frac{\partial \theta(X)}{\partial X_i} \frac{\partial \theta(X)}{\partial X_j}$$  \hspace{1cm} (8)

the FIM in its corresponding AOA positioning can be expressed as:

$$J_{i,j}(\theta(X)) = \nabla^T \theta(X) R_v^{-1} \nabla \theta(X)$$  \hspace{1cm} (9)

That is:

$$J_{i,j}(\theta(X)) = \begin{cases} \sum_{i=1}^{N} \sin^2 \theta_i / \alpha_i^4 & \text{if } i = j \\ \sum_{i=1}^{N} \sin \theta_i \cos \theta_i / \alpha_i^4 & \text{if } i \neq j \end{cases}$$  \hspace{1cm} (10)

here $\alpha = \frac{\lambda}{SNR_0 \cdot l_i}$, and in formula (7), $J_{i,j}(e_i)$ represents FIM of positioning error, which can be specifically expressed as:

$$J_{i,j}(e_i) = \frac{1}{2} \text{Tr} \left[ R_v^{-1}(X) \frac{\partial R_v(X)}{\partial x_i} R_v^{-1}(X) \frac{\partial R_v(X)}{\partial x_j} \right]$$  \hspace{1cm} (11)

among which:

$$\frac{\partial R_v(X)}{\partial x_i} = 2\alpha \cdot \text{diag} \left[ l_1 \cos \theta_1, l_2 \cos \theta_2, ..., l_N \cos \theta_N \right]$$  \hspace{1cm} (12)

$$\frac{\partial R_v(X)}{\partial x_2} = 2\alpha \cdot \text{diag} \left[ l_1 \sin \theta_1, l_2 \sin \theta_2, ..., l_N \sin \theta_N \right]$$

From the above deduction, it can be concluded that the whole FIM with distance-related noise in AOA positioning model is:

$$J = \begin{bmatrix} \sum_{i=1}^{N} \frac{\sin \theta_i}{\alpha_i^4} & \sum_{i=1}^{N} \frac{\cos \theta_i}{\alpha_i^4} & \cdots & \sum_{i=1}^{N} \frac{\sin \theta_i}{\alpha_i^4} \\ \sum_{i=1}^{N} \frac{\sin \theta_i \cos \theta_i}{\alpha_i^4} & \sum_{i=1}^{N} \frac{\cos \theta_i}{\alpha_i^4} & \cdots & \sum_{i=1}^{N} \frac{\sin \theta_i \cos \theta_i}{\alpha_i^4} \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{i=1}^{N} \frac{\sin \theta_i \cos \theta_i}{\alpha_i^4} & \sum_{i=1}^{N} \frac{\cos \theta_i}{\alpha_i^4} & \cdots & \sum_{i=1}^{N} \frac{\sin \theta_i \cos \theta_i}{\alpha_i^4} \end{bmatrix}$$  \hspace{1cm} (13)

here, for the convenience of calculation, the above formula can be simplified, and if $b_i = -\frac{1}{\alpha_i^4} + \frac{2}{l_i}$ and $b_i = \frac{1}{\alpha_i^4} + \frac{2}{l_i}$ are defined, then $J$ can be simplified as:

$$J = \begin{bmatrix} \sum_{i=1}^{N} b_i & \sum_{i=1}^{N} b_i \cos 2\theta_i & \cdots & \sum_{i=1}^{N} b_i \\ \sum_{i=1}^{N} b_i \cos 2\theta_i & \sum_{i=1}^{N} b_i & \cdots & \sum_{i=1}^{N} b_i \cos 2\theta_i \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{i=1}^{N} b_i \cos 2\theta_i & \sum_{i=1}^{N} b_i & \cdots & \sum_{i=1}^{N} b_i \cos 2\theta_i \end{bmatrix}$$  \hspace{1cm} (14)

Therefore, the determinant of FIM can be expressed as:

$$\det(J) = \sum_{i=1}^{N} \sum_{j=1}^{N} 4b_i b_j \sin^2(\theta_i - \theta_j) + \left( \sum_{i=1}^{N} b_i \right)^2 - \left( \sum_{i=1}^{N} b_i \right)^2$$  \hspace{1cm} (15)

and the final required CRLB expression is:
CRLB = \frac{1}{\text{det}(J)} \begin{bmatrix} J_{22} & -J_{12} \\ -J_{21} & J_{11} \end{bmatrix} \tag{16}

IV. PATH OPTIMIZATION OF UAV SWARM

In actual target positioning and tracking, the positioning accuracy is affected by the spatial geometry of the target and UAV Swarm, the measurement error and other factors, among which the spatial geometry of the target and UAV Swarm has a great influence on the positioning accuracy [31], so it is particularly important to plan the real-time flight path of UAV group when actually positioning the target.

A.A-OPTIMALITY CRITERION

A-optimality criterion [32] is to use the trace of CRLB matrix as a standard to measure the positioning performance. The specific method is to minimize the trace of CRLB matrix, namely:

\[ A = \arg \min tr(J^{-1}) \tag{17} \]

Traditional D-optimization criterion [33] is used to minimize the area of the confidence region relative to the estimated parameters. In some cases, the minimization of the volume will produce considerable positioning errors. Compared with d optimization criterion, A-optimality criterion is to solve the trace of CRLB matrix, which is equivalent to directly solving the mean square error (MSE). Under the criterion of A-optimality, the trace of CRLB matrix located by AOA is deduced as follows:

\[ tr(J^{-1}) = \frac{\sum_{i=1}^{N} b_i}{\sum_{i=1}^{N} \sum_{j=1}^{N} 4h_ih_j \sin^2(\theta_i - \theta_j) + \left( \sum_{i=1}^{N} b_i \right)^2 - \left( \sum_{i=1}^{N} h_i \right)^2} \tag{18} \]

For convenience, the above formula can be simplified as:

\[ tr(J^{-1}) = \frac{\sum_{i=1}^{N} b_i}{\text{det}(J)} \tag{19} \]

According to equation (17), under A-optimality criterion, when the value of \( tr(J^{-1}) \) is minimized, the spatial geometric position of UAV Swarm can achieve the optimal deployment. According to the observation formula (18), the positioning accuracy and spatial optimal location deployment of UAV Swarm are related to parameters \( \theta_i \) and \( I_i \), which indicates that the optimal spatial location deployment of UAV Swarm can be realized by changing the positioning angle and distance between UAV Swarm and the measured target, so as to improve the positioning accuracy.

B. ANALYSIS OF FLIGHT ANGLE CHANGE OF UAV SWARM

For the convenience of research and analysis, when \( N = 3 \) is taken, the flight angle of UAV positioning is analyzed, and if \( I_i \) is arbitrarily given and determined, because the maximum eigenvalue of FIM corresponds to the minimum value of CRLB trace, that is, when \( \text{det}(J) \) takes the maximum value, the optimal solution can be obtained, so the optimization problem can be simplified as:

\[ \arg \max_{\theta_i \in (0, \pi)} f(\theta) = \sum_{i=1}^{N} 4h_i \sin^2(\theta_i - \theta) + \left( \sum_{i=1}^{N} b_i \right)^2 - \left( \sum_{i=1}^{N} h_i \right)^2 \tag{20} \]

At this time, the objective function corresponding to the three UAVs can be expressed as:

\[ f(\theta) = \left( \sum_{i=1}^{N} h_i \right)^2 + 4h_i \sin^2(\theta_i - \theta) + 4h_i \left[ b_i \sin^2(\theta_i) + b_i \sin^2(\theta_i) \right] \tag{21} \]

To solve the final angle value, the partial derivative of \( \theta_{12} \) is obtained in the above formula:

\[ 2h_ih_2 \sin(\theta_{12}) \cos(\theta_{12}) - 2h_ih_2 \sin(\theta_{13}) \cos(\theta_{13}) = 0 \tag{22} \]

In the same way, partial derivative of \( \theta_{13} \) can get [18]:

\[ 2h_ih_3 \sin(\theta_{13}) \cos(\theta_{13}) - 2h_ih_3 \sin(\theta_{12}) \cos(\theta_{12}) = 0 \tag{23} \]

The flight angle between each UAV and the target in UAV Swarm can be obtained by solving the simultaneous equations of (22) and (23), assuming that when

\[ -\frac{1}{n}a_i^2 + \frac{2}{l_i^2} \leq \sum_{i=1}^{N} -\frac{1}{a_i^2} + \frac{2}{l_i^2}, n \in \{1,2,3\} \]

the solution results are as follows:

\[ \begin{align*}
\theta_{12} &= \frac{1}{2} \arccos \left( \frac{h_2^2 - h_1^2 - h_3^2}{2h_1h_3} \right) \\
\theta_{13} &= 2\pi - \theta_{12} - \theta_{13} \\
\theta_{23} &= \frac{1}{2} \arccos \left( \frac{h_3^2 - h_1^2 - h_2^2}{2h_2h_3} \right)
\end{align*} \tag{24} \]

When \( -\frac{1}{n}a_i^2 + \frac{2}{l_i^2} \geq \sum_{i=1}^{N} -\frac{1}{a_i^2} + \frac{2}{l_i^2}, n \in \{1,2,3\} \), it is easy to prove that \( f(\theta) \) has a maximum solution if and only if:

\[ \theta_{\text{max}} = \pm \frac{\pi}{2}, s = \{1,2,3\} \setminus n \tag{25} \]

In formula (25), \( \setminus \) is the set subtraction number. According to the analysis of the above formula, in two-dimensional space, when the \( N \) UAV is in the opposite direction to other unmanned aerial vehicles, the error covariance of the measured value is the smallest, and then the optimal situation is reached.
For unmanned aerial vehicles equipped with receiving sensors, when \( N \geq 3 \), the FIM constraint conditions of the special spatial distribution with equal distance (i.e. \( l_1 = l_2 = \ldots = l_N = l \)) are as follows:

\[
f(\theta) \leq \frac{N^2}{4} \left( \frac{2}{l} + \frac{1}{\cos^2 \theta} \right)^2
\]

(26)

The above formula holds for:

\[
\begin{align*}
\sum_{i=1}^{N} \cos(2\theta_i) &= 0 \\
\sum_{i=1}^{N} \sin(2\theta_i) &= 0
\end{align*}
\]

(27)

The two optimal spatial configurations of UAV Swarm with special angle distribution corresponding to the above formula are:

1) Equiangular distribution configuration
   Suppose \( \forall i, j \in \{1,2,\ldots,N\} \) and \( i+1 = j \), then we can obtain:
   \[
   \theta_{ij} = \theta_{ji} = \frac{2\pi}{N}
   \]
   (28)

2) Non-equiaangular distribution configuration
   Suppose \( \forall i, j \in \{1,2,\ldots,N\} \) and \( i+1 = j \), then we can obtain:
   \[
   \theta_{ij} = \theta_{ji} = \frac{\pi}{N}
   \]
   (29)

Compared with other positioning systems, for UAV Swarm, the difference of AOA positioning system is that it can obtain the optimal configuration not only under the equiaangular distribution of UAV, but also under the non-equiaangular distribution [34].

In order to further reflect the theoretical results of spatial configuration analysis, the FIM eigenvalues of three UAVs are calculated and simulated.

\[
\text{FIGURE 3. FIM eigenvalue changes of Swarm composed of three UAVs}
\]

(a) FIM eigenvalue function diagram for Swarm composed of three UAVs (b) FIM eigenvalue contour map of Swarm composed of three UAVs.

Suppose \( l_1 = l_2 = l_3 = 1 \), Fig. 3(a) shows the FIM eigenvalue function diagram when three unmanned aerial vehicles are used for positioning, and Fig. 3(b) shows the FIM eigenvalue contour diagram when three unmanned aerial vehicles are used for positioning, wherein the maximum value is indicated by "+". It can be seen from Fig. 3 that when \( \{\theta_1, \theta_2, \theta_3\} \) is \( \{60^\circ,120^\circ\}, \{60^\circ,300^\circ\}, \{120^\circ,60^\circ\}, \{120^\circ,240^\circ\}, \{240^\circ,120^\circ\}, \{240^\circ,300^\circ\}, \{300^\circ,60^\circ\}, \{300^\circ,240^\circ\} \), the maximum value is 1.25.

To sum up, the optimal angular spacing of UAV Swarm provides an angle judgment basis for the optimal configuration of UAV Swarm. When the angle change needs to be considered, the optimal angle distribution of UAV Swarm becomes not unique, that is, there is the optimal configuration of UAV with unequal angle distribution, and the configuration is affected by the distance \( l \) between UAV Swarm and the measured target.

C. ANALYSIS OF UAV Swarm FLIGHT DISTANCE CHANGE

When the angle \( \theta \) of UAV Swarm is given arbitrarily, the objective function can be simplified as:

\[
\begin{align*}
\text{arg}\min f(l) &= \left( \sum_{i=1}^{N} b_i \right)^	op \left( \frac{1}{2} \sum_{i=1}^{N} d_i \sin \theta_i \cos \theta_i \right) - \frac{1}{2} \sum_{i=1}^{N} d_i \cos 2\theta_i
\end{align*}
\]

(30)

Where \( \theta_i \) is any given value. Therefore, when UAV angle \( \theta \) is given arbitrarily, the smaller the distance between UAV Swarm and the measured target, the larger the trace of CRLB corresponding to UAV Swarm. When \( l_i = l_{\min}, i \in \{1,2,\ldots,N\} \), the obtained objective function \( f(l) \) is the maximum.

According to the above analysis, when the UAV Swarm approaches the measured target, the optimal deployment of UAV Swarm can be realized by selecting an optimal angular spacing. By analyzing the changes of flight angle and flight distance of UAV Swarm, we can know the
specific optimization performance of UAV Swarm, and lay a foundation for real-time planning of UAV track points.

**D.REAL-TIME PATH OPTIMIZATION OF UAV Swarm**

In the last part, the derivation process of A-optimality criterion is mainly given, and the constraint of UAV Swarm with sensor receiver is not considered in the condition assumption. However, in the actual positioning and tracking process, UAV Swarm is affected by its own constraints, and there is no way to achieve the optimal positioning configuration of the measured target in a short time [35-36]. Especially, in the absence of prior information of the measured target, the UAV Swarm must change the searching configuration method for the full detection area into the positioning configuration method for the key targets and areas. At a certain moment, the distance between the UAV Swarm and the measured target may be far away. Considering the flight speed and steering angular velocity of the UAV, it takes a certain amount of time for the UAV Swarm to achieve the optimal positioning configuration. Therefore, the optimal position configuration deployment at each moment can be achieved by real-time route planning of the relative position between UAV Swarm and the target, so as to improve the real-time positioning accuracy of the measured target.

To solve the path planning problem of UAV Swarm, it is assumed that the discrete dynamic model of UAV Swarm system is [37]:

\[
X_{k+1} = f(X_k, U_k), k \in \{1,2,\ldots,N\} \tag{31}
\]

In this formula, \(X_k = [x_1(k), x_2(k), \ldots, x_n(k)]^T\) is the state value of UAV Swarm system at time \(k\) and \(U_k = [u_1(k), u_2(k), \ldots, u_n(k)]\) is the control quantity of UAV Swarm flight azimuth at time \(k\), so the motion equation of UAV Swarm in discrete case can be obtained as follows:

\[
X_k(k+1) = \left[\begin{array}{c}
x_y(k) \\ y_v(k)
\end{array}\right] + v_0T\left[\begin{array}{c}
\cos u(k) \\ \sin u(k)
\end{array}\right] \tag{32}
\]

In the above formula, \(v_0\) is the flight speed of UAV, and \(T\) is the sampling time interval of sensor.

**FIGURE 4. Schematic diagram of UAV Swarm searching for optimal track point**

As shown in Fig. 4, for UAV Swarm, in each sampling time, it uses AOA positioning algorithm to locate the spatial position of the measured target, and takes A-optimality criterion as the optimization objective function. Under this condition, the control quantity \(U_i(k+1)\) of the optimal track point of UAV at the next moment is obtained, and the objective function can be expressed as:

\[
\begin{align*}
\text{arg min } f(U_i(k+1)) &= \text{Tr}(J_i^\top(l_i, \theta))), \quad k \leq 3 \\
\text{arg min } f(U_i(k+1)) &= \text{Tr}(P_i^\top(j_k, l_i, \theta))), \quad k > 3 
\end{align*} \tag{33}
\]

Azimuth constraint conditions of UAV platform are as follows:

\[
\|U_i(k+1) - U_i(k)\| \leq U_{\text{max}} \tag{34}
\]

The above formula mainly limits the maximum deflection angle of the course generated by UAV, and this constraint condition depends on the maneuverability of UAV platform.

\[
G_{ij}(U_i(k)) = R_h - \|X_i(k+1) - \hat{X}_i(k)\| \geq 0 \tag{35}
\]

Equations (35) and (36) respectively represent the distance constraint between UAV Swarm and the measured target. The upper limit of distance \(R_h\) is mainly determined by the signal-to-noise ratio of the UAV receiving signal, and the lower limit of distance \(R_i\) is the safe distance between UAV Swarm and the measured target.

\[
G_{ij}(U_i(k)) = \|X_i(k+1) - X_j(k+1)\| \geq c_i \tag{37}
\]

Equations (35) and (36) are anti-collision constraints of UAV platforms in UAV Swarm and communication constraints between UAV platforms, respectively. For UAV Swarm using AOA positioning algorithm and A-optimality criterion, its specific real-time track planning flow chart is shown in Fig. 5, and its specific data processing steps are as follows:

Step 1: Estimate and calculate the spatial position of the measured target according to the location algorithm such as the maximum likelihood (ML) estimator[38].

Step 2: The objective function is continuously combined and optimized, and then the objective function is calculated...
by A-optimality criterion, that is, finding the minimum value of CRLB matrix trace.

Step 3: Real-time planning of the heading angle of the UAV at the next moment by searching the optimal heading angle.

Step 4: When the UAV flies to the optimal track point at the next moment, continue to use AOA positioning algorithm to estimate the spatial position of the measured target.

FIGURE 5. Flow chart of UAV Swarm positioning and track planning

V. SIMULATION EXPERIMENT

In the experimental simulation stage, three UAVs are used to locate and measure the measured target, and the initial space position state of the UAVs at the initial time is assumed as follows:

\[ X_i(0) = [x_i, y_i, z_i, \theta_i]^T \]

The spatial position states of each UAV at the initial time are

\[ X_1(0) = [-8000, 0, -6000, 0]^T \]
\[ X_2(0) = [-10000, 0, -5000, 0]^T \]
\[ X_3(0) = [-9000, 0, -5000, 0]^T \]

respectively. The initial position of the target is the origin of coordinate axis. At the initial time, the flight direction of each UAV is \( y \) axis, and the flight speed is \( v = 140 \text{ m/s} \), the total simulation time is \( T = 1 \text{s} \), and the sampling time interval is \( 70 \text{s} \). It is assumed that the measurement variance per unit distance of UAV mounted sensors is \( \sigma^2 = 0.1 \), the minimum and maximum interception distances of UAV in UAV Swarm are \( R_l = 300 \text{m} \) and \( R_h = 20000 \text{m} \), and the heading angle constraint is \( \theta_{\text{max}} = 15^\circ \). Communication distance between UAVs in UAV Swarm is about \( c_h = 15000 \text{m} \), and anti-collision constraint is \( c_l = 200 \text{m} \).

A. TARGET STATIONARY
Fig. 6(a) is the track diagram of three unmanned aerial vehicles flying straight towards the target without path optimization. Fig. 6(b) is the path optimization positioning track map of UAV with A-optimality criterion as the objective function. It can be seen from the figure that all three UAVs are affected by angle criterion. In order to achieve reasonable station deployment, the included angle between UAV 2 and UAV 3 and UAV 1 is expanding continuously during flight. When the three UAVs get a certain angle, they start to fly towards the target under the influence of distance criterion, and reduce the distance between them, so as to achieve the balance between the final angle criterion and distance criterion. By comparing Fig. 6(c), Fig. 6(d) and Tab. 1, it can be seen that the distance between UAV and target is decreasing because UAV without path optimization is flying towards the target, and its positioning error generally shows a downward trend due to the influence of distance criterion. Compared with UAV positioning with path optimization, the positioning accuracy of UAV with path optimization is obviously higher than that without path optimization. The main reason is that UAV positioning with path optimization not only considers the distance criterion, but also constantly adjusts the real-time angle change of UAV flight through A-optimality criterion to reach the balance point between angle criterion and distance criterion. Thereby realizing optimal real-time positioning, greatly reducing positioning errors and improving positioning stability.

TABLE 1. Comparison of path optimization positioning errors for AOA positioning of stationary targets by three UAVs

| Target stationary       | Mean value of positioning error | 607.501 m |
|-------------------------|---------------------------------|---------|
| Without path optimization| Minimum positioning error       | 24.067 m |
|                         | Standard deviation of positioning error | 985.451 m |
| With path optimization  | Mean value of positioning error | 501.938 m |
|                         | Minimum positioning error       | 6.200 m  |

B. TARGET MOVEMENTS

When the target is in motion, the motion state of the target is divided into four states: uniform linear motion, variable acceleration linear motion, uniform circular motion and complex curve motion. Assume that the target moves in a straight line with a speed of \( v_0 = 70 \text{ m/s} \). When the target moves in a straight line with variable acceleration, the moving speed of the target is 1.02 times that of the previous moment. When the target moves in a uniform circular motion, its state transition matrix is:

\[
F_s = \begin{bmatrix}
1 & \sin(\omega T) & 0 & -(1 - \cos(\omega T)) \\
0 & \cos(\omega T) & 0 & -\sin(\omega T) \\
0 & (1 - \cos(\omega T)) & 1 & \sin(\omega T) \\
0 & \sin(\omega T) & 0 & \cos(\omega T)
\end{bmatrix}
\]

where \( \omega = 0.5 \). When the target moves in a complex curve, its state transition matrix is a combination of several curve motion state transition matrices, which are not listed here, and other constraints are consistent with the stationary target.

1) THE TARGET MOVES IN A UNIFORM STRAIGHT LINE

![Graph showing the movement of targets and UAVs](image)
In Fig. 7(a) and Fig. 7(b) are divided into flight path maps with or without path optimization when three unmanned aerial vehicles locate a target moving in a straight line at a constant speed. It can be seen from the Fig. 7(a) that without path optimization, the three unmanned aerial vehicles move in a constant straight line towards the measured target in a fixed direction; In Fig. 7(b), when there is path optimization, the angles of the three UAVs begin to change at the initial stage, and the angle between UAV 1 and UAV 3 is gradually widened. After the angle gradually changes and a certain angle is obtained, the distance from the target is gradually reduced according to the distance criterion, so as to achieve the optimal track deployment. Comparing Fig. 7(c), Fig. 7(d) and Tab. 2, it can be seen that the average value of positioning error with path optimization is 251.429 meters, and the minimum value of positioning error is 1.403 meters, which is obviously smaller than that without path optimization.

**TABLE 2. Comparison of AOA positioning errors with or without path optimization for three UAVs in uniform linear motion target**

|                  | Without path optimization | With path optimization |
|------------------|---------------------------|------------------------|
| Mean value of positioning error | 475.975 m                | 251.429 m              |
| Minimum positioning error         | 21.067 m                  | 1.403 m                |
| Standard deviation of positioning error | 641.401 m            | 454.329 m              |

2) **THE TARGET CHANGES AND ACCELERATES STRAIGHT-LINE MOTION**
moving target, and when there is no path optimization, the three UAVs fly at a constant speed in a fixed direction, as shown in Fig. 8(a). It can be seen from Fig. 8(b) that in the initial stage, in order to obtain more angle information, the angle between UAV 1 and UAV 3 and UAV 2 is gradually widened. After obtaining certain angle information, the distance criterion is considered, and the distance between UAV and the measured target is gradually reduced to complete path optimization. Comparing Fig. 8(c), Fig. 8(d) and Tab. 3, the positioning error of UAV with path optimization is obviously smaller than that without path optimization.

\begin{table}[h]
\centering
\caption{Comparison of AOA positioning errors with or without path optimization for three unmanned aerial vehicles with variable acceleration linear moving targets}
\begin{tabular}{|c|c|c|}
\hline
& Without path optimization & With path optimization \\
\hline
Mean value of positioning error & 381.927 m & 251.429 m \\
Minimum positioning error & 31.969 m & 15.975 m \\
Standard deviation of positioning error & 337.301 m & 219.392 m \\
\hline
\end{tabular}
\end{table}

3) THE TARGET MOVES IN A UNIFORM CIRCULAR MOTION

In Fig. 8(a) and Fig. 8(b) are divided into flight path maps with or without path optimization when three UAVs carry out AOA positioning on a variable acceleration linear
In Fig. 9(a) and Fig. 9(b) are respectively divided into flight path diagrams with or without path optimization when three UAVs perform AOA positioning on a target with uniform circular motion. Fig. 9(a) shows three UAVs flying in a fixed direction without path optimization, and Fig. 9(b) shows three UAVs performing AOA positioning on the measured target with path optimization. It can be seen from the figure that at the initial stage, the three UAVs constantly change their respective angles in order to obtain enough angle information, and when certain angle information is obtained, they begin to reduce the distance between them and the measured target. However, due to the circular motion of the target, its direction angle information also changes in real time. The three UAVs need to change their angle in real time while reducing the distance between them and the target, and adjust the flight path of the UAV in real time at the next moment, finally realizing the path optimization of the UAV. It can be seen from Fig. 9(c) and Fig. 9(d) that the UAV without path optimization flies in a fixed direction without considering the change of its own angle and distance, and its positioning error generally shows a trend of increasing first and then decreasing gradually, and the positioning error fluctuates greatly. However, because the UAV with path optimization constantly adjusts and changes the angle of UAV and the distance between UAV and the measured target, and makes track planning in real time, its positioning error generally shows a downward trend and is relatively stable. It can be seen from Tab. 4 that the average positioning error of UAV without path optimization is 3067.698 meters, while that of UAV with path optimization is 199.816 meters. It can be seen from this. Path optimization of unmanned aerial vehicle (UAV) with A-optimality criterion as its objective function greatly improves the positioning accuracy of the target moving in a uniform circle, effectively reduces the positioning error of UAV, and keeps the positioning accuracy stable.

**TABLE 4. Comparison of AOA positioning errors with or without path optimization for three UAVs in uniform circular motion target**

| Without path optimization | Mean value of positioning error | 3067.698 m |
|---------------------------|--------------------------------|------------|
| Minimum positioning error | 15.807 m                       |
| Standard deviation of positioning error | 2363.877 m |
With path optimization

Mean value of positioning error 199.816 m
Minimum positioning error 3.279 m
Standard deviation of positioning error 380.549 m

4) THE TARGET MOVES IN A COMPLEX CURVE

In Fig. 10(a) and Fig. 10(b) are respectively divided into flight path diagrams with or without path optimization when three UAVs locate complex curved moving targets in AOA, and Fig. 10(a) is without path optimization, when three UAVs fly at a constant speed in a fixed direction to locate the measured targets; Fig. 10(b) shows path optimization. At this time, three UAVs use AOA-optimality criterion as the objective function to locate the target. It can be seen from the figure that the three UAVs collected more angle information at the initial time. UAV 1 and UAV 3 gradually increase the angle between UAV 2 and UAV 1, and begin to reduce the distance between UAV and the measured target after obtaining certain angle information. However, because the direction and distance of the target are changing all the time, the UAV is gradually reducing the distance between the UAV and the target, and at the same time changing the flight direction of the UAV in real time according to the position change of the target, thus making real-time flight path planning for the UAV and improving the positioning accuracy. It can be seen from Fig. 10(c), Fig. 10(d) and Tab. 5 that the positioning error of UAV with path optimization is obviously lower than that without path optimization, and the positioning accuracy of UAV with path optimization is stable.

TABLE 5. Comparison of AOA positioning errors with or without path optimization for moving targets with complex curves by three UAVs

|                         | With path optimization | Without path optimization |
|-------------------------|------------------------|---------------------------|
| Mean value of positioning error | 199.816 m              | 200.000 m                 |
| Minimum positioning error   | 3.279 m                | 5.000 m                   |
| Standard deviation of positioning error | 380.549 m             | 390.000 m                |
The Target Moves in a Complex Curve

|                      | Without path optimization | With path optimization |
|----------------------|---------------------------|------------------------|
| Mean value of        | 756.853 m                 | 312.915 m              |
| positioning error    |                           |                        |
| Minimum positioning  | 67.452 m                  | 1.856 m                |
| error                |                           |                        |
| Standard deviation   | 952.563 m                 | 424.401 m              |
| of positioning error |                           |                        |

V. Conclusion

In this paper, an AOA positioning algorithm based on path optimization criterion is proposed to solve the problem of UAV Swarm locating targets in various motion states under the condition that the noise variance changes with distance, and the UAV Swarm is optimized in real time. Firstly, the AOA positioning model and the distance-dependent noise model of UAV Swarm are established. Secondly, the positioning accuracy of AOA positioning is analyzed by CRLB, and the A-optimality criterion under this model is derived theoretically. In this paper, the changes of flight angle and flight distance of UAV under this model are analyzed in detail, and the real-time flight path planning of UAV at the next moment is carried out with the minimum value of CRLB matrix trace as the objective function. The simulation results show that the track optimization can improve the positioning accuracy and stability of UAV swarm for multiple moving targets. This study only models and simulates the multi-target motion state of a single target, and does not consider the multi-target situation under the conditions of complex terrain and strong electromagnetic interference. Therefore, the research has certain limitations. In the next step, we can look forward to the positioning and tracking of multi-target under the conditions of complex environment.

DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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