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A Near-Field Target Localization Method for MIMO Radar

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Abstract—The existing target localization algorithms almost cannot be used to near-field target localization in Multiple-Input Multiple-Output (MIMO) radar, and this paper presents a novel method. This algorithm uses Chan algorithm to obtain initial estimate of the targets. Then we define a new residual matrix and use the weighted least square (WLS) method to get a more accurate positioning result. The Fuzzy C-Means (FCM) algorithm is introduced to get more stable and accurate estimation. Furthermore, this algorithm achieves accurate positioning of the MIMO radar demonstrated by simulations.

1. INTRODUCTION

Accurate positioning of the target is one of the basic functions of radar [1, 2], and MIMO radar's [3, 4] research and application are to promote the development of this function. In a MIMO system, the transmitting and receiving antennas are separated and distributed evenly, which can illuminate the target in all directions and overcome the fluctuation of the target (radar crossing section) RCS. There are many algorithms for radar target location, but most of them assume that the target is located in the far field, and they receive and process the plane wave. But when the target is close to the transmitter and receiver antennas, this assumption will no longer be established because the waveform is spherical. In recent years, low angle targets, such as the stealth machine, often appear as the development of the stealth technology, and they are easy to enter the near field without being found [5–8].

Positioning technology based on signal transmission time is one of the most extensive technologies. Among them, time difference of arrival (TDOA) [9] algorithm attracts more attention because of its low complexity, easy implementation, etc. TDOA's core technology based on the time difference is to calculate distance and solve the positioning equations so that target location can be obtained. The position equations have nonlinear characteristics, which usually need to be converted to linear equations. Then Chan algorithm [10] and WLS are used to solve the modified equations and give a non iterative closed solution. This method has the best estimation performance when TDOA measurement error is relatively small, but its performance will degrade rapidly while the error is increasing.

Classification is carried out by clustering [11] on a certain rules or specific criteria (such as distance criterion). During classification, large similar data are merged into the same class, putting the small similar data into different classes. Traditional clustering is a kind of hard clustering, which strictly puts an object within a certain range, and the range of membership function is $\{0, 1\}$. However, lots of objects' classification boundary are not clear in reality, and we need appropriate methods for soft partition, so that people put forward the concept of fuzzy clustering, which uses membership function to show that it has the tendency of intermediate transition, and its range of the membership function of fuzzy function is $[0, 1]$. The basic idea of the FCM algorithm for fuzzy mean clustering is to classify the given data with some criteria and think that each datum is a certain probability. It usually gives

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out object function J and divides datum by J's minimum value as criterion. Also, the best membership U and best fuzzy clustering center V of each type of data can be found.

In this paper, target locations are carried out in the near field with MIMO radar. It writes TDOA equations according to data from receiving antennas, then using Chan algorithm combined with WLS algorithm to get the initial estimate. After that, considering the correlation between the target position and the target transmit/receive position, a residual matrix is introduced, and the WLS algorithm is used to deal with the error again. Finally, in order to obtain relatively stable and accurate estimation of the target, this paper uses the FCM algorithm to cluster processing.

2. SYSTEM MODEL AND LOCATION METHOD

Considering a two-dimension situation, there are M transmitters and N receivers in a MIMO radar system. The coordinates of transmitters are (x_{tk}, y_{tk}), $k = 1, 2, \ldots, M$, and those of receivers are (x_{rl}, y_{rl}), $l = 1, 2, \ldots, N$. In this paper, the subscripts t and r are used to denote the transmitter and receiver, respectively. Let us define the receiver N as reference, and its coordinate is (x_{tN}, y_{rN}). When we observe the MIMO radar from receiver N, there are M paths from all transmitters to receiver N, so we can take it as multiple-input single-output (MISO) radar. In this paper, we set one path as reference, and other $M - 1$ paths subtract the reference path. In this paper, we choose the transmitters M as reference and the distance between the target and transmitters as

$$d_{tk} = \sqrt{(x - x_{tk})^2 + (y - y_{tk})^2}, \quad k = 1, 2, \ldots, M \tag{1}$$

And the distance between the target and receivers can be expressed as

$$d_{rl} = \sqrt{(x - x_{rl})^2 + (y - y_{rl})^2}, \quad l = 1, 2, \ldots, N \tag{2}$$

Defining difference in distance between d_{tk} and d_M as d_{kN} and also considering the influence of noise, then

$$d_{kM} = c\tau_k = (d_{tk} + d_{rl}) - (d_{tT} + d_{rl}) + \bar{n}_l \tag{3}$$

where $c = 3 \times 10^8$ m/s, which is the speed of electromagnetic wave propagation in space, and estimate error n_l is independent and identically distributed $(i.i.d)$ with zero mean and variance σ^2, which is $\bar{n}_l \sim (0, \frac{\sigma^2}{N})$. Since $(d_{kM} + d_{tT})^2 = (d_{tk})^2$, we can obtain

$$w = b - Aa \tag{4}$$

which $A = \begin{bmatrix} x_{1M} - x & y_{1M} - y & d_{1M} \\ x_{2M} - x & y_{2M} - y & d_{2M} \\ \cdots & \cdots & \cdots \\ x_{(M-1)M} - x & y_{(M-1)M} - y & d_{(M-1)M} \end{bmatrix}$, $a = \begin{bmatrix} x & y & d_{tM} \end{bmatrix}^T$, $b = \begin{bmatrix} b_1 & b_2 & \ldots & b_M \end{bmatrix}^T$, $b_k = \frac{1}{2}(d_{kM}^2 - x_{tk}^2 - y_{tk}^2 + x_{tM}^2 + y_{tM}^2)$, $k = 1, 2, \ldots, M - 1$; $\varphi = -B\bar{n} + 0.5\bar{n} \otimes \bar{n}$, which $\otimes$ represents Schur product, $B = \text{diag}\{d_{t1}, d_{t2}, \ldots, d_{t(M-1)}\}$, and $\bar{n} = [\bar{n}_1, \bar{n}_2, \ldots, \bar{n}_{M-1}]$;

Let us denote noise covariance matrix as

$$\psi = BQB \tag{5}$$

Since n_i is $i.i.d$,

$$Q = E\left(\bar{n}\bar{n}^T\right) = \frac{1}{N}\text{diag}\left(\sigma^2, \sigma^2, \ldots, \sigma^2\right) = \frac{\sigma^2}{N} I \tag{6}$$

where I is unit matrix.

Assuming elements in a are independent, Eq. (4) is a linear equation. Using Chan algorithm, which does not need an initial position for equations, can deal with the above equations with WLS algorithm [12, 13]. The result is

$$\hat{a}_0 = \left(A_0^T \psi_0^{-1} A_0\right)^{-1} A_0^T \psi_0^{-1} b \tag{7}$$

According to Equation (7), we can get the first target location.

The premise of the above algorithm is that the target transmitter/receiver positions are not related to the target position, but in fact they are related. Therefore, defining a new residual matrix ε:

$$\varepsilon = h - G\theta \tag{8}$$

where $h = [(\hat{x}_0 - x_{tk})^2, (\hat{y}_0 - y_{tk})^2, \hat{d}_N]^T$, which contains $\hat{x}_0$, $\hat{y}_0$, $\hat{d}_{N1}$ from Equation (7), $G = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$, $\theta = \begin{bmatrix} (x - x_{tk})^2 \\ (y - y_{tk})^2 \end{bmatrix}$. Using WLS again, one can obtain

$$\hat{a}_1 = \left(A_1^T \psi_1 A_1\right)^{-1} A_0^T \psi_1^{-1} h \tag{9}$$

where $\psi_1 = \begin{bmatrix} \varepsilon & \varepsilon^T \end{bmatrix}$, $A_1 = \begin{bmatrix} x_{1M} - \hat{x}_0 & y_{1M} - \hat{y}_0 & d'_{1M} \\ x_{2M} - \hat{x}_0 & y_{2M} - \hat{y}_0 & d'_{2M} \\ \cdots & \cdots & \cdots \\ x_{(M-1)M} - \hat{x}_0 & y_{(M-1)M} - \hat{y}_0 & d'_{(M-1)M} \end{bmatrix}$,

$d'_{kM} = -\sqrt{(\hat{x}_0 - x_{tM})^2 + (\hat{y}_0 - y_{tM})^2} + \sqrt{(\hat{x}_0 - x_{rl})^2 + (\hat{y}_0 - y_{rl})^2}$, $k = 1, 2, \ldots, M-1$. Thus the optimal solution is obtained.

In order to obtain more accurate and stable estimates, this paper introduces the fuzzy C-mean (FCM) algorithm [14] in the case of considering the computational error. This algorithm sets the estimated value of the calculation to the object X, and X is divided into C classes. Assuming that cluster center is $V = \{v_1, v_2, \ldots, v_C\}$, the objective function of FCM algorithm is

$$J(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{C} (\mu_{ij})^m \|x_i - v_i\|^2 \tag{10}$$

The minimum value of $J(U,V)$ is the clustering criterion and under the constraint of $\sum_{i=1}^{C} u_{ij} = 1$ with Lagrange multiplier method,

$$v_j = \sum_{i=1}^{N} \mu_{ij}^m x_i \Big/ \sum_{i=1}^{N} \mu_{ij}^m \tag{11}$$

$$\mu_{ij} = \left[\sum_{k=1}^{C} \left(\frac{\|x_i - v_j\|^2}{\|x_i - v_k\|^2} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{12}$$

where m is the fuzzy weighted index. Formula continues iterating until the objective function reaches a predetermined threshold.

Algorithm steps are as follows,

Step 1: Give the number of clusters C, set the iteration stop value ε and initialize the cluster center — $V^{(n)}$, where n is the number of iteration.

Step 2: Update fuzzy matrix $U^{(n)}$.

$$\mu_{ij}^n = \left[\sum_{k=1}^{C} \left(\frac{\left\|x_i - v_j^{(n)}\right\|^2}{\left\|x_i - v_k^{(n)}\right\|^2} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{13}$$

Step 3: Update cluster center matrix

$$v_j^{(n+1)} = \sum_{i=1}^{N} (\mu_{ij}^{(n)})^m x_i \Big/ \sum_{i=1}^{N} (\mu_{ij}^n)^m \tag{14}$$

Step 4: If $\|V^{(n+1)} - V^{(n)}\| \leq \varepsilon$, the algorithm ends and center matrix V and fuzzy matrix U are exported. Otherwise, turn to step 2.

In this paper, we set that the number of clusters is 100; iteration termination condition $1e-5$, cluster center 2, besides number of iteration is 100. After the data are brought into the FCM algorithm, we get two clustering centers and take the mean value of the two cluster centers as the final estimate of the target position.

3. SIMULATION AND ALGORITHM ANALYSIS

Let us define the four transmitters and four receivers approximately located on a circle with a diameter of 50 km, and the actual position of the target is $(-30000\,\text{m}, 40000\,\text{m})$. The positions of receivers and results are independent of each other, because we obtain TDOAs through calculating the difference of TOAs from any one receiver. TDOA errors n_l are $i.i.d$, and the variance $\sigma = 10\,\text{ns}$. The performance of FCM algorithm can be found in Figure 1. Here, we use 100 data for location estimation, and after two WLS estimates, the estimated target location is set to two clustering points for clustering. From Figure 1, we can see that two clustering centers are basically symmetrical with respect to the target position. Thus, we can get a more accurate estimate. Compared to not using FCM algorithm, the effect of adding FCM algorithm is shown in Figure 2. It is easy to find that within a certain range of σ, the

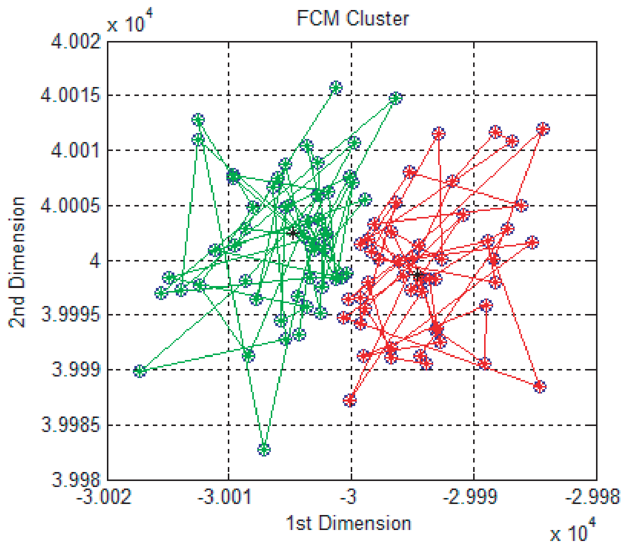

Figure 1. FCM algorithm.

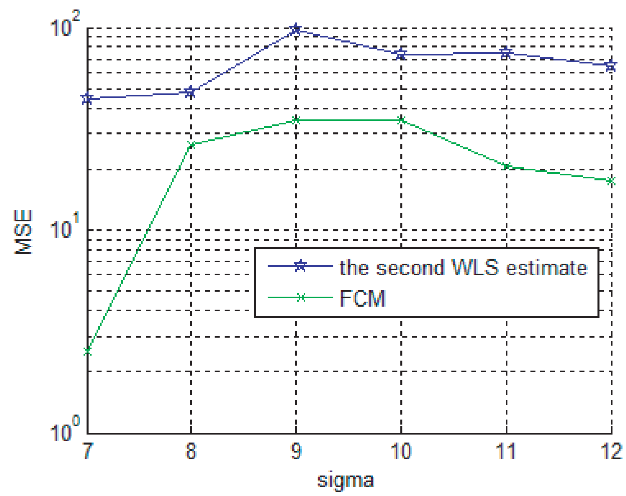

Figure 2. MSE.

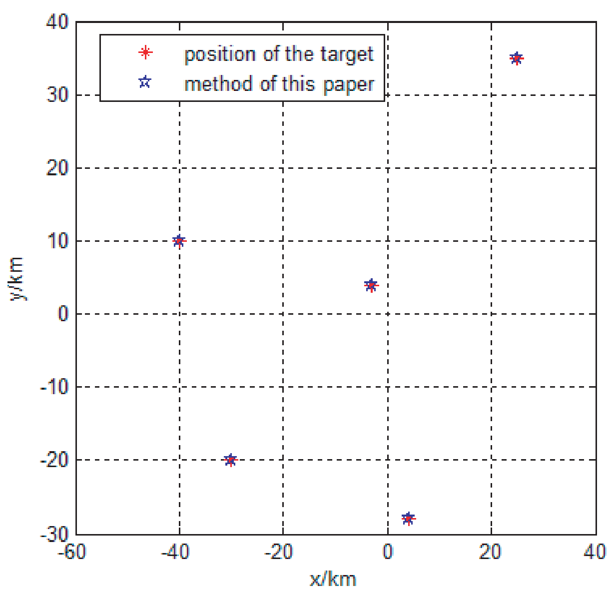

Figure 3. Positioning effect.

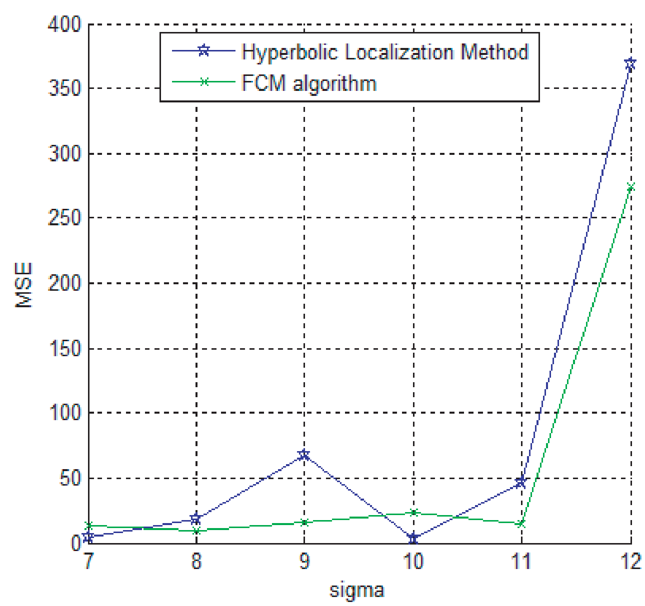

Figure 4. Comparison between localization methods.

positioning is more accurate after the FCM algorithm processing, and the target location estimation algorithm is feasible in this paper.

In order to demonstrate the feasibility of the proposed method, we set several different targets, and the coordinates of targets are (−40 km, 10 km), (−3 km, 4 km), (25 km, 35 km), (4 km, −28 km), (−30 km, −20 km), respectively. From Figure 3, it is easy to see that the positioning results coincide with the actual position of the target. On the other hand, it means that this method is available. Furthermore, as shown in Figure 4, compared to the method of [12], which obtains equations of TDOA as a linear form and uses BLUE and partly Taylor expansion method to estimate the target position, the method of this paper within a certain range of σ is more stable and accurate.

4. CONCLUSION

Conventional localization methods in MIMO radar are almost adapted to the far-field, and this paper presents another effective method for near-field target localization in a MIMO radar. We obtain initial estimations of the targets by using Chan algorithm, and subsequently we introduce a new residual matrix to improve estimations. FCM algorithm is used to get a more accurate result than Hyperbolic Localization Method, and the result is more stable. However, moving targets are not considered in this article, although they must be significant in practice. The related work will be further finished.

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