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A NOVEL DATA ASSOCIATION ALGORITHM BASED ON FCM-DFA

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Abstract. *In order to obtain higher correct correlation rate under the condition of high track density in multiple target tracking system, it is very necessary to improve association accuracy. In this paper, a data association algorithm based on fuzzy c-means clustering (FCM) and discriminative feature algorithm (DFA) is presented. Every time the membership degree matrix between measurements and clustering center will be computed. Membership degree matrix is designed to represent the association degree between the measurements and tracks. According to the maximal element of each sensor's membership degree matrix, if the measurement is not associated with any track, the discriminative feature will be utilized to determine the measurement ownership. The proposed algorithm is realized in the simulation experiment, which compares FCM-DFA with the nearest neighbors data association algorithm (NNDA), and the simulation result indicates that the proposed algorithm has better correlation rate when the tracks are crossed and the tracking accuracy is better.*

Keywords: Multi-target tracking, Data association, Fuzzy c-means clustering, Discriminative model

1. Introduction.

Multi-sensor information fusion of multiple target tracking problem can be described as optimizing two related functions about associate and estimate. In heavily cluttered environment, there is too much uncertainty about the tracking measurements. Data association problem is one of the most important problems in data fusion [1], and it is the precondition of realizing multi-sensor multi-target-tracking. At present, a global best track correlation algorithm is proposed in [2], by using global search and gating to improve the correct association rate. [3] calculated likelihood values and similarity index for each observation obtained by radar, and expectation maximization technique is applied to obtaining possibility association matrix. As for fuzzy correlation of tracks, [4] used multi-factor fuzzy integration decision and made several mathematic models to apply the algorithm to different type of sensors. [5] imported the evidence theory into track association, modified the subjection regulation to acquire evidence information, and then disposed the information based on evidence theory. A joint optimization algorithm for tracking and track association is accomplished by solving the problem of track interlace when single sensor tracks closely spaced objects [6]. A nearest neighbor data association algorithm which based on the minimum normalized distance is proposed to correlate tracks for close target [7].

However, almost all of those works focus on improving correct correlation rate in the simple simulation environment. In this paper, the data association algorithm based on fuzzy c-means (FCM) clustering and discriminative feature algorithm (DFA) is presented for multiple target tracking.

By setting up separate data correlation algorithm in each sensor observation, multiple target tracking is simplified to single target tracking problem. In this paper, association will not only be accomplished by single membership matrix, but also the maximal element's position of each membership degree matrixes will be compared, and then discriminative feature would be imported to make further judgment.

2. FCM and Discriminative Feature.

2.1. Fuzzy c-means clustering algorithm. FCM is a method that can automatically classify the data sample [8,9]. By optimizing fuzzy aim function to obtain the membership degree of sample points and cluster center, determine the belonging of the sample points.

There is a limited collection in S dimension space, $X = \{x_1, x_2, \ldots, x_n\} \in R^s$ indicates there are n collections of samples for clustering, x_k $(k = 1, 2, \ldots, n)$ is the sample point, the number of the system tracks is c, cluster center is $V = \{v_1, v_2, \ldots, v_c\}^T \in R^s$, U is a partition matrix of elements u_{ik}. u_{ik} represents the degree of membership of data point k in fuzzy cluster center i.

$$0 \leq u_{ik} \leq 1 \tag{1}$$

Here: $1 \leq i \leq c$, $1 \leq k \leq n$.

$$\sum_{i=1}^{c} u_{ik} = 1 \quad \forall k \tag{2}$$

$$0 < \sum_{i=1}^{n} u_{ik} < n \quad \forall i \tag{3}$$

Define the aim function J_m as follows:

$$J_m(U, V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m \left|x_k - v_i\right|^2 \tag{4}$$

Weighted index number m is a real number called the fuzzification constant, and $m \in [1, \infty)$. The step of FCM is as follows.

1) Initialize the convergence criterion $\varepsilon > 0$, setting cluster center $V^{(0)}$ randomly, let $k = 1$, and compute U^k.

$$u_{ik} = \frac{1}{\left[\sum\limits_{j=1}^{c} \left(\frac{|x_k - v_i|}{|x_k - v_j|}\right)^{2/(m-1)}\right]} \quad \forall i, k \tag{5}$$

2) Computation of $V^{(k+1)}$.

$$v_i = \frac{\sum\limits_{k=1}^{n} (u_{ik})^m x_k}{\left[\sum\limits_{k=1}^{n} (u_{ik})^m\right]} \quad \forall i \tag{6}$$

3) If $\left|V^{(k+1)} - V^{(k)}\right| < \varepsilon$, the iteration will be stopped, otherwise $k = k + 1$ and turn to calculate U^{k+1}, until satisfying the convergence condition as above mentioned.

Based on above analysis, the aim of FCM algorithm is to determine the optimum degrees of membership u_{ik} and the optimum fuzzy cluster centers v_i, so FCM algorithm is guaranteed to converge to a local minimum. The choice of fuzzification constant m plays an important role on the fuzzy degree of clustering. When $m = 1$, it is hard clustering, When $m > 1$, it is fuzzy c-means clustering, in this paper $m = 2$.

In this paper, the improved FCM algorithm is utilized [10]. The noisy data points could be assigned to the noise class, and it conforms to the actual heavily cluttered radar environment. So modify the above FCM as follows:

$$\sum_{i=1}^{c+1} u_{ik} = 1 \quad \forall k \tag{7}$$

$$J_m(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c+1} (u_{ik})^m \left| x_k - v_i \right|^2 \tag{8}$$

$$u_{ik} = \frac{1}{\left[\sum_{j=1}^{c+1} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)} \right]} \quad \forall i, k \tag{9}$$

In the multiple target tracking system, the sample point is the measurements which get from sensors, and c is the track number. Cluster center is track prediction value $\hat{Z}$, d_{ik} is Mahalanobis distance. u_{ik} is the track association degree of the ith measurement and the kth track.

2.2. **Import discriminative feature.** The above mentioned method is to solve the problem between measurements and tracks, but if the tracks are crossed, it will increase the possibility of error association in heavily cluttered environment, as the vector's non-similarity indicator of FCM is obtained by Mahalanobis distance. The crossed targets are illustrated in Figure 1. The point 1 should be associated with trace 1; however, when association only depends on single sensor's membership degree matrix, point 2 will associate with trace 1. After the discriminative feature, such as the attributes of velocity, direction of motion and target are imported, even if the Mahalanobis distance is minimum, the association will not fail on account of different motion attribution.

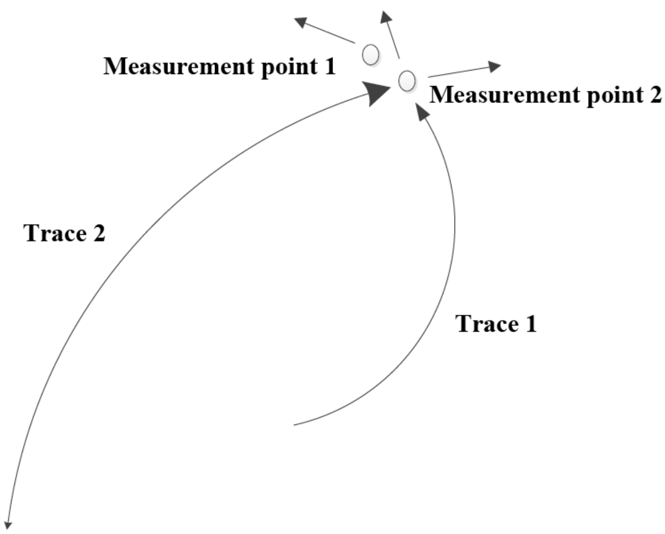

Figure 1. The scene of error association

Thus discriminative feature should be imported to reduce the wrong association possibility. The system receives track messages not the measurements of sensors. The track message includes position, type, velocity, and direction of motion, error and other characteristic value of tracks.

$Y = [n_1, n_2, n_3, \ldots, n_s]$ is the state eigenvector of target, s is the dimension of eigenvector. $Y_{I_j}(t)$ indicates the eigenvector prediction of track j of sensor I at time k. Let feature threshold vector $E = [e_1, e_2, e_3, \ldots, e_k]$.

If the track j of sensor I associated with the track n of sensor M, it should satisfy the follow conditions:

$$\begin{cases} \min : dis(Y_{I_j}(t)l, Y_{M_n}(t)l), \quad M \neq I, \quad n = 1, 2, \ldots, k_m \\ \left|Y_{I_j}(t) - Y_{M_n}(t)\right| < e_i, \quad i = 1, 2, \ldots, k \end{cases} \tag{10}$$

Distance formula is as follows:

$$dis(l_1, l_2) = \left[(l_1x - l_2x)^2 + (l_1y - l_2y)^2 + (l_1z - l_2z)^2\right]^{1/2} \tag{11}$$

In this function, $dis(l_1, l_2)$ is the cartesian distance; $\left|Y_{I_j}(t) - Y_{M_n}(t)\right| < e_i$ presents the difference value of the attributes of two prediction states within the presupposed threshold value, if $\left(\left|u_{I_j - M_n}(1,t)\right| < e_1\right) \cap \left(\left|u_{I_j - M_n}(2,t)\right| < e_2\right) \cap \ldots \cap \left(\left|u_{I_j - M_n}(k,t)\right| < e_k\right)$ the judgment of attribute relative is true otherwise return false.

3. Description of Data Association Algorithm Based on FCM-DFA.

In the data association process, the same set of target tracks will be projected to separate observation space of each sensor to get the measurements prediction; on this basis, different sensors can establish relatively independent data association algorithm. Due to the fact that the single sensor data association algorithm includes the same target tracks, multi target data association and multi sensor data fusion can improve the tracking accuracy. For FCM algorithm, the prediction value of tracks will be transformed to the observation space of each sensor as their clustering center, and then the measurements will be associated with tracks. The entire multi sensor data association algorithm will be presented as follows.

Let sensor number $s = 1, \ldots, N_s$, the measurement amount is m_{k_i} $(i = 1, 2, \ldots, N_s)$.

At time t_k, the aggregate of the measurements of N sensors is

$$Z(k) = \left(Z_1^1(k), \ldots, Z_{m_{k1}}^1(k), Z_1^2(k), \ldots, Z_{m_{k2}}^2(k), \ldots, Z_1^N(k), \ldots, Z_{m_{N_s}}^N(k)\right) \tag{12}$$

T tracks are assumed in the observation space.

Step 1. When the track update cycle begins, track file will show the position and velocity of object after smoothed, the predicted position and velocity will be given by filter. If the sensor could directly give the position measurement in the rectangular coordinate system turn to Step 2, otherwise it should be converted to the rectangular coordinate system.

Step 2. According to the target measurements and prediction value of target position, associated matrix $U^1_{T\times m_{kq}}$ can be obtained by (9) which is based on Mahalanobis distance.

Step 3. Repeat Step 2, associated matrix U^s $(s == 1, 2, \ldots, N_s)$ of N_s sensors will be established.

Step 4. Find the maximal element u_{ij} of each matrix. u_{ij} represents the degree of membership of measurement j in fuzzy cluster center i, in this paper, fuzzy cluster center is the prediction value given by extended Kalman filter (EKF) [11]. When every sensor associate measurement j with track i, the association could be confirmed; otherwise discriminative feature will be combined with associate matrixes to complete the final association. Then let u_{ij} become 0 and repeat the above method until all tracks associated.

4. Simulation Result and Analyses.

In this section, Monte Carlo simulations are performed to analyze the performance of the proposed data association algorithm based on the FCM and discriminative feature. Taking two radar systems for example, in order to simplify the problem, we assume the observation space of the sensors are completely coincidence. The simulation results will show the effectiveness of the algorithm.

4.1. **System modeling.** The dynamical equation of target t is second-order dynamic model.

$$\begin{aligned} X^t(k+1) &= FX^t(k) + V^t(k) \\ Z^t(k+1) &= h(X^t(k+1)) + W^t(k+1) \\ E\left\{V^t(k)V^t(j)'\right\} &= Q^t(k)\delta_{kj} \\ E\left\{W^t(k)W^t(j)'\right\} &= R^t(k)\delta_{kj} \end{aligned} \tag{13}$$

δ_{kj} is Kronecker delta function, where $X^t(k) = [x(k) \quad \dot{x}(k) \quad y(k) \quad \dot{y}(k)]$ is state variable, where $V^t(k)$ and $W^t(k+1)$ are respectively stationary white noise processes with covariance matrices $Q^t(k)$ and $R^t(k)$. Radars are located at position $(x_{m,s}, y_{m,s})$. The measurement $(r_{m,s}, \theta_{m,s})$ equations of each sensor are given by

$$\begin{aligned} r_{m,s} &= \sqrt{(x - x_{m,s})^2 + (y - y_{m,s})^2} + \upsilon_{1,s} \\ \theta_{m,s} &= \tan^{-1}\left(\frac{y - y_{m,s}}{x - x_{m,s}}\right) + \upsilon_{2,s} \end{aligned} \tag{14}$$

where $\upsilon_{k,s} = [\upsilon_{1,s} \;\; \upsilon_{2,s}]^T$ is the measurement noise vector.

4.2. **Trajectory design.** To simplify the problem, coordinate transformation and time-alignment will not be considered, and both radars are synchronous, which are located in rectangular coordinate origin. In the simulation, sampling period $T = 1$s, detection probability $P_d = 1$. The initial value of filter will be given by the information of the former two sampling points. 3 targets are supposed to be at a constant speed of cross motion. The initial state for the target trajectory and the initial estimate for the filters are given by $x_0^1 = [1452, 281.9, 8565, 102.6]$, $x_0^2 = [1000, 300, 5000, 0]$, $x_0^3 = [1452, 281.9, 3435, -102.6]$. A priori state covariance matrix is given by $P_0^1 = P_0^2 = P_0^3 = diag([10000, 100, 10000, 100])$, and the process noise variance is set to

$$Q_0^1 = Q_0^2 = Q_0^3 = \begin{bmatrix} 0.125 & 0.25 & 0 & 0 \\ 0.25 & 0.5 & 0 & 0 \\ 0 & 0 & 0.125 & 0.25 \\ 0 & 0 & 0.25 & 0.125 \end{bmatrix}$$

The measurement noise variance can be represented as: $R^1 = R^2 = R^3 = diag(10000, 10000)$.

4.3. **Comparison of tracking performance.** The performance of the proposed FCM-DFA is compared with the NNDA in terms of the estimation accuracy for multiple sensor estimation. Figure 2 and Figure 3 show the target trajectories in 50s which are realized by FCM-DFA and NNDA respectively.

The root-mean-square error (RMSE) of time k during the whole tracking process can be formulated as (15):

$$\mathrm{RMSE}(k) = \sqrt{\frac{1}{M_c}\sum_{m=1}^{M_c}(x_k - \hat{x}_k^m)^2} \tag{15}$$

where M_c is the number of the Monte-Carlo simulation, $M_c = 50$; x_k is the true state of the system, $\hat{x}_k^m$ is the estimated vector at the mth simulation.

Figure 4 to Figure 6 describe the range RMSE of the proposed method and NNDA during the tracking. From the comparison, we can see that the proposed FCM-DFA method presents more excellent tracking accuracy. As the NNDA algorithm is based on the minimum normalized distance, which may make error association when tracks are crossed, the proposed method could solve that problem to get better correlation rate. When the tracks are crossed, the performance of FCM-DFA remained unaffected. It is

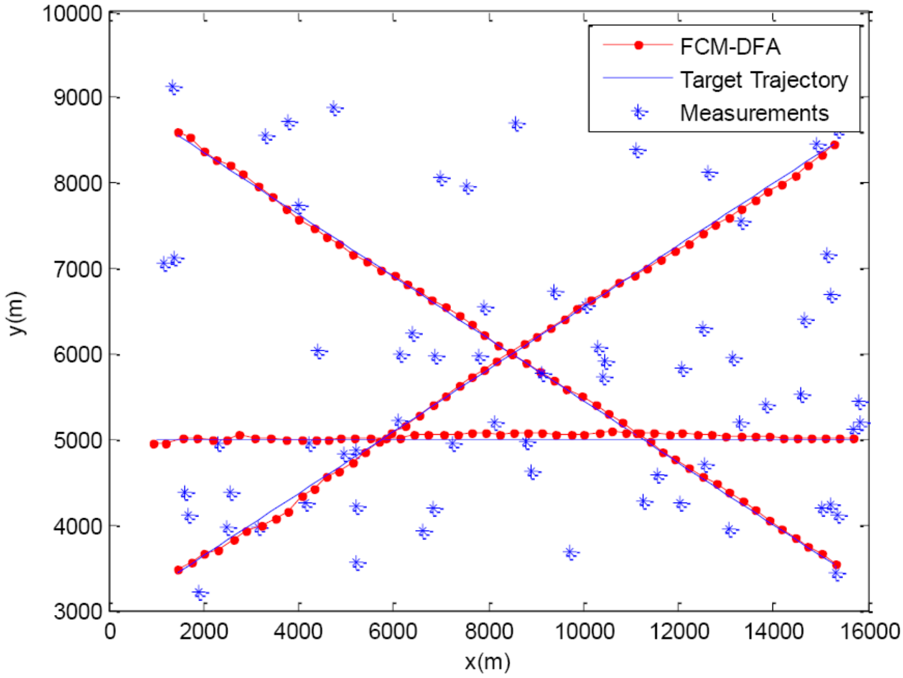

Figure 2. Target tracked by FCM-DFA

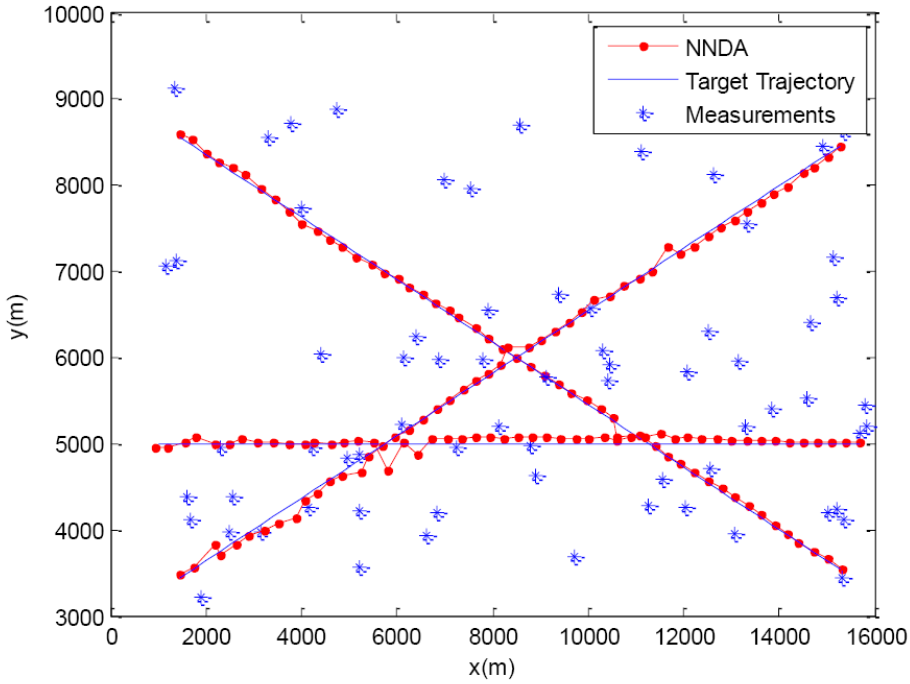

Figure 3. Target tracked by NNDA

because that we decompose multi sensor system into single sensor problem and utilize discriminative feature to confirm the association.

5. **Conclusion.** In this paper, we have presented a new strategy of data association based on the proposed FCM-DFA method in the radar network. For multiple sensor information fusion multi target tracking system, by building projection of multiple target motion state in different sensor observation space, multi sensor correlation decomposes into single sensor correlation; in this process, computational complexity will be reduced and due to the fact that discriminative feature is imported, the stability of association

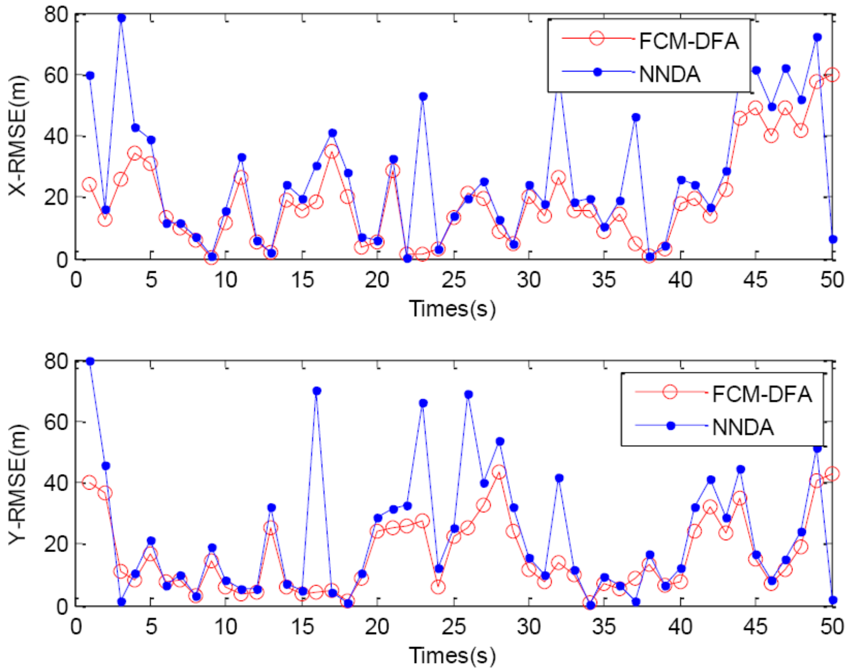

Figure 4. RMSE of target1

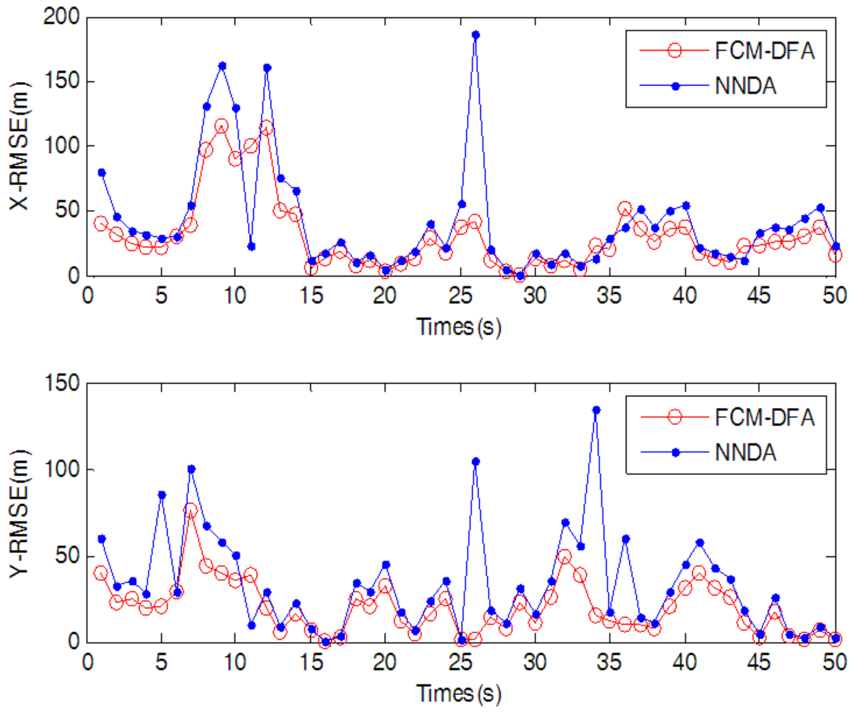

Figure 5. RMSE of target2

process will be enhanced. In the future work, improved fuzzy clustering algorithm will be used to initiate new tracks adaptively as well as combination and separation of the tracks.

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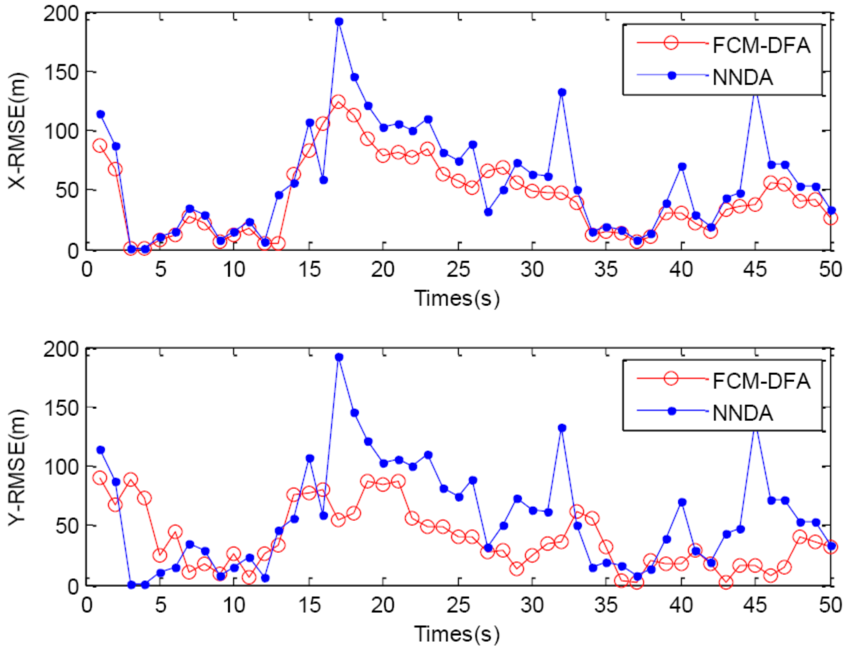

FIGURE 6. RMSE of target3

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