Advanced Technique based on Nearest Neighbor for Tracking Closed Spaced Targets in Clutter

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Abstract

The In this paper, a new technique named optimum nearest neighbor data association (ONNDA) is proposed to overcome the tracking issue of closed spaced moving targets in dense clutter environment. The proposed algorithm detects the measurements that represent the valid targets from all measurements in the cluttered gate. A new virtual gate is assigned to the detected valid measurements. The center of this gate is represented by the last point of the tracked target position. In this new gate the nearest neighbor data association algorithm is used to select the true measurement that represent the moving target. The ONNDA detects the candidate measurement with the lowest probability of error, increases the data association performance compared to nearest neighbor (NN) filter, and detects the closed moving targets in more background clutter. Simulation results show the effectiveness and better performance when compared to conventional algorithm as NNKF.

Key Words: *kalman filter, multi-target tracking, moving target indicator, nearest neighbor data association*

1. Introduction

In Multiple Target Tracking (MTT) system, data association and tracking filter are two basic parts of tracking objects. The performance of a tracking filter relies heavily on the use of the data association technique. So, the data association is an important key in tracking system to associate the track to the true target in noisy received measurements. The data association problem during tracking targets has been described. While tracking targets, usually multiple measurements received from rotating sensor may be originated from true targets or from false alarm (measurement noise) or clutter. The incorrect measurements that are referred to as false measurements or clutter are the main problem to data association process. To deal with problem, many techniques [1,2] of data association need to select the measurement that most probable is originated from the target to be tracked. If the wrong measurement is selected, or if the correct measurement is not detected at all, poor state estimates could be the result. Another problem in case of tracking multiple targets, data association becomes more difficult because one measurement can be validated by multiple tracks in addition to, a track validating multiple measurements as in the single target case. To solve these problems, the important of an alternative approaches known as nearest neighbor data association (NNDA) [3-6], probabilistic data association (PDA) [7,8], joint probabilistic data association (JPDA) [9-11], and multiple hypothesis Tracking (MHT) [12,13], etc. have been used to track multiple targets by evaluating the measurement to track association probabilities with different methods to find the state estimate [14]. PDA, JPDA and MHT need prior knowledge and some of them have large calculation amount [5],[15-17]. NNDA that depends only on choosing the nearest valid measurement to the predicted target position, has been used in real work widely because of its low computational cost, most simple, most popular suggestion for its implementation [5]. But the nearest neighbor approach will associate correctly the true measurement only in the case when this measurement lies closer to the predicted target position than the false return. Thus NN performs poorly both in moderate to high numbers of clutter measurements or with closely spaced targets.

We propose here a new technique to update the conventional NNDA to be able to track the multi-target with closed space in dense clutter environment. This proposed algorithm is more accurate to choose the true measurement originated from the target with lower probability of error than NNDA algorithm. The new technique is divided into two parts. The first part is depending on the basic principle of moving target indicator (MTI) filter used in radar signal processing [18-20],[23]. This part get rid from the fixed targets and the targets that moving with lower velocity and their moving distance lower than specified certain threshold value. This reduces the number of candidate measurements in the gate by comparing the moving distance measure for each measurement in the current gate to all previous measurements in the same gate. Due to comparison, any measurement in the current gate that moves a distance less than the threshold value may be avoided. Thus, decreasing the number of candidate measurements in the current gate lead to decreasing the probability of error in data association process. The second part uses nearest neighbor algorithm (NN) that is depending on selecting the valid measurement that has a minimum distance in a virtual current gate. This virtual gate contains all valid measurements with a center related to the last position of the tracked target instead of the estimated tracked target position (the center of the current gate). The last position of the tracked target is updated each scan and is refer to optimum measurement in the previous tracked target gate. This method is called optimum nearest neighbor data association (ONNDA) method which is more accurate than NNDA algorithm to track the moving closed spaced targets in presence of various clutter densities. Simulation results showed better performance when compared to the conventional NNKF algorithm.

2. Background

2.1 Kalman Filter

Based on Kalman filter estimation [21], we list the filter model. The dynamic state and measurement model of target *t* can be represented as follows

$$\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}) = \boldsymbol{A}^{\boldsymbol{t}}(\boldsymbol{k}-1)\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}-1) + \boldsymbol{w}^{\boldsymbol{t}}(\boldsymbol{k}-1) \qquad \boldsymbol{t} = 1,2,\ldots,\boldsymbol{T} \tag{1}$$

$$\boldsymbol{z}^{\boldsymbol{t}}(\boldsymbol{k}) = \boldsymbol{H}^{\boldsymbol{t}}(\boldsymbol{k})\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}) + \boldsymbol{v}^{\boldsymbol{t}}(\boldsymbol{k}) \qquad \boldsymbol{t} = 1,2..\boldsymbol{T} \tag{2}$$

Where $\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}-1)$ is the *n* x *1* target state vector. This state can include the position and velocity of the target in space $\boldsymbol{x} = (\boldsymbol{x}, \boldsymbol{y}, \dot{\boldsymbol{x}}, \dot{\boldsymbol{y}})'$, The initial target state, $\boldsymbol{x}^{\boldsymbol{t}}(0)$ for *t* = *1*,*2***,** ..., *T* , is assumed to be Gaussian With mean $\boldsymbol{m}_0^{\boldsymbol{t}}$ and known covariance matrix $\boldsymbol{p}_0^{\boldsymbol{t}}$. Where the unobserved signal (hidden states) $\left\{\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}) : \boldsymbol{k} \in \boldsymbol{N}\right\}, \boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}) \in \boldsymbol{X}$ be modeled as a Markov process of transition probability $\boldsymbol{p}\left(\boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}) \mid \boldsymbol{x}^{\boldsymbol{t}}(\boldsymbol{k}-1)\right)$ and initial distribution $\boldsymbol{p}\left(\boldsymbol{x}^{\boldsymbol{t}}(0)\right)$ $= \boldsymbol{N}(\boldsymbol{x}^{\boldsymbol{t}}(0); \boldsymbol{m}_0^{\boldsymbol{t}}, \boldsymbol{p}_0^{\boldsymbol{t}})$. $\boldsymbol{z}^{\boldsymbol{t}}(\boldsymbol{k})$ is the *m* **x** 1 measurement vector, $\boldsymbol{A}^{\boldsymbol{t}}(\boldsymbol{k}-1)$ denotes state transition matrix, $\boldsymbol{H}^{\boldsymbol{t}}(\boldsymbol{k})$ denotes measurement matrix, $\boldsymbol{w}^{\boldsymbol{t}}(\boldsymbol{k}-1)$ and $\boldsymbol{v}^{\boldsymbol{t}}(\boldsymbol{k})$ are mutually independent white Gaussian noise with zero mean, and with covariance matrix $\boldsymbol{Q}(k\text{-}1)$ and $\boldsymbol{R}(k)$, respectively. The innovation mean (residual error) of measurement $z_i(k)$ is given by

$$V_i^t(k) = z_i(k) - \hat{z}^t(k) \tag{3}$$

where

$$\hat{z}^t(k) = H^t(k)\overline{m}^t(k) \tag{4}$$

and the predicted state mean and covariance is defined as

$$\overline{m}^t(k) = A^t(k)m^t(k-1) \tag{5}$$

and

$$\overline{p}^t(k) = A^t(k)p^t(k-1)A^t(k)' + Q \tag{6}$$

Then, we can update state by

$$m^t(k) = \overline{m}^t(k) + K^t(k)Vsel(k) \tag{7}$$

where $Vsel(k)$ is the selected innovation mean from $V_i^t(k)$ corresponding to the choosing measurement as a result of data association process , $K^t(k)$ denotes gain matrix calculated by state error covariance $p^t(k)$ and innovation covariance $S^t(k)$, their recursive equations can be represented as follows

$$p^t(k) = \overline{p}^t(k) - K^t(k)S^t(K)K^t(k)' \tag{8}$$

$$S^t(K) = H^t(k)\,\overline{p}^t(k)\,H^t(k)' + R(k) \tag{9}$$

$$K^t(k) = \overline{p}^t(k) - H^t(k)S^t(k)^{-1} \tag{10}$$

When multiple target tracking begins, we get for each target *t* measurements within correlation gate (gate size) as candidate measurements when $z_i(k)$ satisfies condition

$$\left(z_i(k) - H^t(k)\overline{m}^t(k)\right)' S^t(k)^{-1}\left(z_i(k) - H^t(k)\overline{m}^t(k)\right) \le \gamma \tag{11}$$

where γ denotes correlation gate. If there is only one measurement, this can be used for track update directly; otherwise if there is more than one measurement, we need to calculate the equivalent measurement.

2.2 Nearest Neighbor Kalman Filter

The NNKF is theoretically the most simple single-scan recursive tracking algorithm. The NNKF consists of a discrete-time Kalman filter (KF) together with a measurement selection rule. The NNKF takes the KF's state estimate $\hat{x}(k-1 \mid k-1)$ and its error covariance $P(k-1 \mid k-1)$ at time $k-1$ and linearly predicts them to time k. The prediction is then used to determine a validation gate in the measurement space based on the measurement prediction $\hat{\boldsymbol{z}}^{\boldsymbol{t}}(\boldsymbol{k} \mid \boldsymbol{k}-1)$ and its covariance $S(k)$. When more than one measurement $\boldsymbol{z_i}(\boldsymbol{k})$ fall inside the gate, the closest one to the prediction is used to update the filter. The metric used is the chi-squared distance:

$$d_i^t(k)^2 = \left(V_i^t\right)' S^t(k)^{-1} \left(V_i^t\right) \le \gamma$$

$$= \left(z_i(k) - \hat{z}^t(k)\right)' S^t(k)^{-1} \left(z_i(k) - \hat{z}^t(k)\right) \le \gamma \quad (12)$$

is calculated to determine the closest measurement by the following.

$$i_{closest} = \underset{i=1\ to\ c^t(k)}{\arg\min} \left\{ d_i^t(k)^2 \right\}_{t=1,2,\ldots T} \quad (13)$$

The subscript i stand for the *ith* measurement associated with target ***t*.** This approach is only mean-square optimal when there are no false alarms and a single target is present. While, if clutter exists, the probability of choosing the correct decision is decreased and may lead to failing tracks. The update corrects the state prediction by a time-varying gain multiplying the difference between the prediction and the actual measurement. The error covariance is also updated (see [22] for further details). This filter is only mean-square optimal when there are no false alarms and a single target is present.

3. Optimum Nearest Neighbor Data Association

Due to, the NNKF suffer from tracking of closed spaced target in dense clutter environment and its performance is degraded with many loss-tracks, a new data association technique called optimum nearest neighbor data association (ONNDA) is introduced to overcome the tracking issue of moving closed spaced targets in clutter. This technique has two processes, the first process based on detecting or distinguishing between the clutter measurements in the gate of the predicted target and the measurements originated from the moving target using two successive scan. The measurements at time *k-1* that lies in the gate of the predicted target position (predict to time *k*) is processed with the measurements at time *k* that lies in the same gate to obtain the valid measurements that is related to true moving targets. This is obtained by calculating the distance metric (a_v_{ij}) more than a specified threshold value (α) between the measurements in the gate at time *k*-1 and measurements in the same gate at time *k* of two successive scan. The threshold value is determined according to the maximum distance metric that is related to maximum speed of false moving target or clutter. The second process is used to select optimum measurement $z_{opt}(k)$ (updated true target) from all valid measurements that are detected by the first process in the gate at time k. This by assigning a virtual gate contain all the valid measurements and then nearest neighbor data association algorithm (NNDA) is used. From the optimum measurement $z_{opt}(k-1)$ that is detected at the previous scan at time *k*-1 (instead of predicted target position $\hat{z}(k)$) the distance metric is calculated to obtain the closest valid measurement as described below .

In this section as shown in figure1, we introduce a new algorithm.

In the prediction step, let $\overline{Z}^t(k-1)=\{z_1(k-1),..z_i(k-1),..z_{m_i}(k-1)\}$ be a set of the candidate points detected in the t^{th} gate $G_t(k-1)$ of predicted position $\hat{z}^t(k)$ where i =1 to mi (number of detected points in gate $G_t(k-1)$ at time *k-1*) and $\overline{Z}^t(k-1)$ be a set of all valid points $z_i(k-1)$ that satisfy the distance measure condition

$$\left(z_i(k-1)-\hat{z}^t(k)\right)' S^t(k)^{-1}\left(z_i(k-1)-\hat{z}^t(k)\right)\le\gamma \quad .(14)$$

for each target t where γ is threshold value that determines the gate size, i is initialized by 1 and is increased by $i = i + 1$ after each valid point is detected up to last mi detected points.

In the updating step, the candidate points detected in the same gate $G_t(k)$ as in $G_t(k-1)$ of the t^{th} predicted position $\hat{z}^t(k)$ be a set of $\overline{Z}^t(k)=\{z_1(k),..z_j(k),..z_{mj}(k)\}$ where j =1 to mj (number of detected points in t^{th} gate at time *k*) and $\overline{Z}^t(k)$ be a set of all valid points $z_j(k)$ that satisfy the distance measure condition

$$\left(z_j(k) - \hat{z}^t(k)\right)' S^t(k)^{-1}\left(z_j(k) - \hat{z}^t(k)\right) \le \gamma \quad (15)$$

for each target t , j =1 to mj and j =j+1 after each valid point is detected.

A filtering method based on the filtering gate structure and moving target indicator [23] is used to distinguish between the detected measurements in $G_t(k)$ that originated from the target or originated from clutter (false target). The nearest of each measurement of x and y component in $G_t(k)$ with its corresponding measurement in $G_t(k-1)$ is obtained by calculating the distance measure between each measurement in $G_t(k)$ and its nearest value. We consider that the measurement in $G_t(k)$ is originated from clutter or false moving target in case its nearest measure not exceed a threshold value α . This is based on calculation of the innovation v_{xij} , v_{yij} and distance metric a_v_{ij} between all detected points $z_i(k-1)$, $z_j(k)$ of x and y component as follow;

$$\begin{aligned} v_{xij} &= z_{xj}(k) - H\, z_{xi}(k-1) \\ v_{yij} &= z_{yj}(k) - H\, z_{yi}(k-1) \end{aligned} \quad (16)$$

$$a\_v_{ij} = \sqrt{{v_{xij}}^2 + {v_{yij}}^2} \quad (17).$$

Each point $z_j(k)$ in $G_t(k)$ has distance metric a_v_{ij} less than threshold value α is related to invalid target {I} that is detected by the following equation

$$\begin{aligned} &\{z_j\} = I \qquad IF \;\; a\_v_{ij} < \alpha \\ &\{z_j\} = V \qquad IF \;\; a\_v_{ij} > \alpha \\ &\qquad i = 1,2,\ldots\ldots mi,\; i \ne opt \\ &\qquad j = 1,2,\ldots\ldots\ldots mj \end{aligned} \quad (18)$$

This calculation divides the measurements in gate $G_t(k)$ into valid target V and invalid target I. One measurement that represents the true target is selected from all measurements in $G_t(k)$ that are related to valid targets V This selection is detected by calculating the distance metric d_v_j between the all valid measurements V and the optimum measurement $z_{opt}(k-1)$ and choosing measurement that has the shortest distance metric by using the NNDA algorithm. The calculation of shortest distance is obtained by the following equation in x and y component.

$$\begin{aligned} \boldsymbol{vd}_{xj} &= \boldsymbol{z}_{xj}(\boldsymbol{k}) - \boldsymbol{H}\,\boldsymbol{z}_{xopt}(\boldsymbol{k}-1) \\ \boldsymbol{vd}_{yj} &= \boldsymbol{z}_{yj}(\boldsymbol{k}) - \boldsymbol{H}\,\boldsymbol{z}_{yopt}(\boldsymbol{k}-1) \end{aligned} \tag{19}$$

$$\boldsymbol{d\_v}_{\boldsymbol{j}} = \sqrt{\boldsymbol{vd}_{xj}^{\;2} + \boldsymbol{vd}_{yj}^{\;2}} \;, \textit{ where } j=1,2,\ldots,vj \tag{20}$$

$$\boldsymbol{j}^{*} = \arg \min_{\boldsymbol{j}=1\,\boldsymbol{to}\,\boldsymbol{vj}} \{\boldsymbol{d\_v}_{\boldsymbol{j}}\} \tag{21}$$

$$\begin{aligned} \boldsymbol{vx}_{\boldsymbol{sel}} &= \boldsymbol{vx}_{\boldsymbol{j}^{*}}(\boldsymbol{k}) \\ \boldsymbol{vy}_{\boldsymbol{sel}} &= \boldsymbol{vy}_{\boldsymbol{j}^{*}}(\boldsymbol{k}) \end{aligned} \tag{22}$$

Where j^{*} is the index of nearest valid measurement that as the minimum distance from the detected optimum measurement $\boldsymbol{z}_{\boldsymbol{opt}}(k\text{-}1)$.

As detecting the index of nearest valid measurement j^{*}, the optimum measurement is updated to be as in the following equation

$$\begin{aligned} \boldsymbol{z}_{\boldsymbol{xopt}}(\boldsymbol{k}) &= \boldsymbol{z}_{\boldsymbol{xj}^{*}}(\boldsymbol{k}) \\ \boldsymbol{z}_{\boldsymbol{yopt}}(\boldsymbol{k}) &= \boldsymbol{z}_{\boldsymbol{yj}^{*}}(\boldsymbol{k}) \end{aligned} \tag{23}$$

Or

$$\boldsymbol{z}_{\boldsymbol{opt}}(\boldsymbol{k}) = \boldsymbol{z}_{\boldsymbol{j}^{*}}(\boldsymbol{k}) \tag{24}$$

There is a special case may be occurred when the number of measurements that is detected in the gate at time k is one in this case the innovation mean $\boldsymbol{v}_{\boldsymbol{j}}$ in x and y component

$$\begin{aligned} \boldsymbol{v}_{xj} &= \boldsymbol{z}_{xj}(\boldsymbol{k}) - \boldsymbol{H}\,\hat{\boldsymbol{z}}_{x}(\boldsymbol{k}) \\ \boldsymbol{v}_{yj} &= \boldsymbol{z}_{yj}(\boldsymbol{k}) - \boldsymbol{H}\,\hat{\boldsymbol{z}}_{y}(\boldsymbol{k}) \end{aligned} \qquad \text{for } \;, j=1 \tag{25}$$

is directly considered as the selected innovation $\boldsymbol{v}_{\boldsymbol{sel}}$ that its measurement is assigned to the optimum measurement $\boldsymbol{z}_{\boldsymbol{opt}}$ as in the following.

$$\left\{ \begin{aligned} & vx_{sel} = vx_{j}(k) \\ & vy_{sel} = vy_{j}(k) \\ & z_{xopt}(k) = z_{xj}\;(k) \\ & z_{yopt}(k) = z_{yj}\;(k) \\ & or\;\; z_{opt}(k) = z_{j}(k) \end{aligned} \right\} for\;\; j=1 \tag{26}$$

The clutter points in two successive gates has little change from time k-1 to k compared to the change of true target point of *x* and *y* component. These gates have the same center that is related to the predicted target position as shown in figure 2 The distance metric (v_{xij}, v_{yij}) in x and y component is calculated between two successive points at time k-1 and k to detect and avoid in the current gate the invalid points that have distance metric less than α . The remaining points are considered to be valid points that have a high probability of true target. From the tracked target position $z_{opt}(k-1)$ at time k-1 we calculate the distance metric (vd_{xj}, vd_{yj}) of the valid points in x and y component and choose the closest one to be considered as the true target. In the final calculation of the current iteration, the optimum point z_{opt} at time *k*-1 is updated to be the selected point that is related to the new tracked target position.

Finally, we obtain the optimum innovation mean (v_{xsel}, v_{ysel}) that is related to the true selected target with decreasing the probability of error and is used in updating target to the correct position. Reducing the number of valid points in the t^{th} gate by detecting the false measurements to be invalid, this increase the probability for choosing the true measurement originated from the target. Using the nearest neighbor algorithm from the last point of tracked target position is more accurate instead of the predicted target position, this improve the quality of data association process.

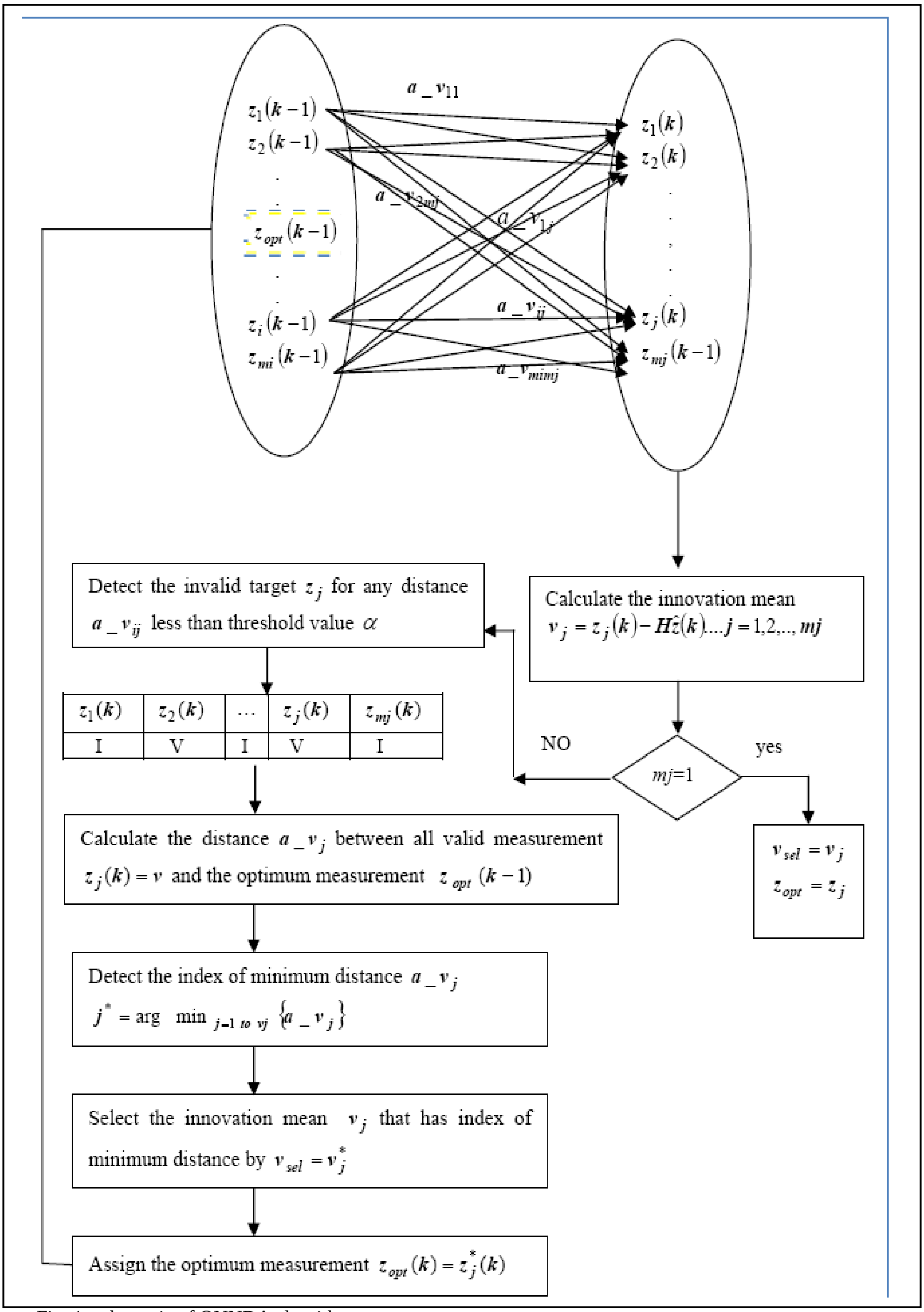

Fig. 1: schematic of ONNDA algorithm

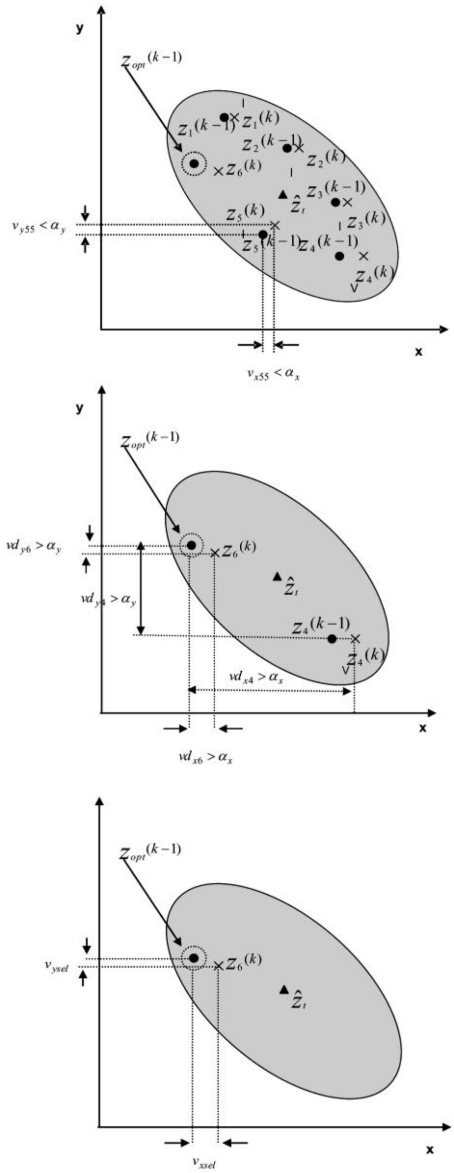

Fig. 2: gate its center is the predicted target position include for example measurements {z1,z2,z3,z4,z5}at time *k* and time *k-1* in x,y coordinate, it is clear that z1(*k*),z2(*k*),z3(*k*),z5(*k*) are measurements originated from clutter while z4(*k*) is a measurement originated from the target.

4. Implementation of Optimum Nearest Neighbor Data Association (ONNDA) using the kalman filter.

In conventional data association approaches based on the current scan, all observations lying inside the tracked target gate are considered in association. The gate may have a large number of observations due to heavy clutter; this leading to the probability of error to associate target-originated measurements may be increased. Another issues, the gate may has more than one moving target that are closest to each other and there is a difficult to distinguish between them, and the one track may associate more than one moving target this lead to error in track estimation and the probability of selecting the true target is poor.

We propose an algorithm which depends on the history of observation for one scan and the basis of moving target indicator (MTI) filter to distinguish between moving target and fixed target or clutter in the tracked target gate. In this proposed algorithm the calculation of innovation mean that is used in update state estimation of the target is more accurate. The calculation of innovation depends on selecting the optimum measurement that is obtained by using the nearest neighbor (NN) algorithm to measure from the last tracked target position instead of predicted target position. The proposed ONNDA using Kalman filter is represented in algorithm 1.

Algorithm 1 **ONNDA** using Kalman filter

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1. for $t = 1$ *to* T do

2. Do prediction step,

$$x^t(k \mid k-1) \sim p\left(x^t(k) \mid Z_{1:k-1}\right) = N\left(x^t(k); \bar{m}^t(k), \bar{p}^t(k)\right) \text{ where}$$

$$\bar{m}^t(k) = A^t(k) m^t(k-1)$$
$$\bar{p}^t(k) = A^t(k) p^t(k-1) A^t(k)' + Q$$

3. Calculate the selected innovation mean $V_{sel}(k)$ that is related to choosing the optimum valid measurement z_{opt}(k) by ONNDA algorithm described in algorithm 2

4. Do update step

$$m^{t}(k) = \overline{m}^{t}(k) + K^{t}(k) V_{sel}(k)$$

$$p^{t}(k) = \overline{p}^{t}(k) - K^{t}(k)\, S^{t}(K)\, K^{t}(k)'$$

$$S^{t}(K) = H^{t}(k)\, \overline{p}^{t}(k)\, H^{t}(k)' + R(K)$$

$$K^{t}(k) = \overline{p}^{t}(k) - H^{t}(K)\, S^{t}(K)^{-1}$$

5. end for

Algorithm 2 Calculate $V_{sel}(k)$ by ONNDA

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1. Find validated region for measurements at time *k*-1:

$$\overline{Z}^{t}(k-1) = \{z_i(k-1)\}, \qquad i = 1,..mi$$

by accepting only those measurements that lie inside the gate *t*:

$$\overline{Z}^{t}(k-1) = \left\{ Z \;:\; \left(z_i(k-1) - H^{t}(k)\overline{m}^{t}(k)\right)' S^{t}(k)^{-1} \left(z_i(k-1) - H^{t}(k)\overline{m}^{t}(k)\right) \leq \gamma \right\}$$

2. Find validated region for measurements at time *k*:

$$\overline{Z}^{t}(k) = \{z_j(k)\}, \qquad j = 1,..mj$$

by accepting only those measurements that lie inside the gate *t*

$$\overline{Z}^{t}(k) = \left\{ Z \;:\; \left(z_j(k) - H^{t}(k)\overline{m}^{t}(k)\right)' S^{t}(k)^{-1} \left(z_j(k) - H^{t}(k)\overline{m}^{t}(k)\right) \leq \gamma \right\}$$

where $s^{t}(k) = H^{t}(k)\overline{P}^{t}(k)H^{t}(k)' + R$

3. Calculate the distance a_v_{ij} between all measurement lie inside the gate *t* at time *k-1(except* z_{opt}(*k*-1)) and *time k* respectively

$$v_{xij} = z_{xj}(k) - H^{t}(k) z_{xi}(k-1)$$

$$v_{yij} = z_{yj}(k) - H^{t}(k) z_{yi}(k-1)$$

$$a\_v_{ij} = \sqrt{{v_{xij}}^2 + {v_{yij}}^2}$$, where *i* =1,2,…*mi* , $i \neq i_{opt}$, j=1,2,…*mj*

4. Detect the valid measurements { z_j } =V for all measurements lie inside the gate t at time k that have a distance $a\_v_{ij} > \alpha$

5. Calculate the distance d_v_j between the valid measurements { z_j } =V detected inside the gate t at time k and the optimum measurement z_{opt}(k-1)

$$vd_{xj} = z_{xj}(k) - H^t(k) z_{xopt}(k-1)$$

$$vd_{yj} = z_{yj}(k) - H^t(k) z_{yopt}(k-1)$$

$$d\_v_j = \sqrt{vd_{xj}^{\,2} + vd_{yj}^{\,2}} \quad , \textit{where } j=1,2,....,vj$$

6. using the NNDA algorithm detect the index of nearest valid measurement $z_j^* \cong z_{opt}(k)$

$$\overset{*}{j} = \arg \min_{j=1\,to\,vj} \{d\_v_j\}$$

and set $z_{opt}(k) = z_j^*(k)$

7. Then calculate the innovation mean $V_{sel}(k)$

$$V_{sel}(k) = z_j^*(k) - H^t(k)\hat{z}(t)$$

5. Simulation Results

Simulation results have been carried out to monitor the performance of the proposed ONNDA algorithm compared to the conventional NNKF. To highlight the performance of the proposed algorithm, we used a synthetic dataset to track four moving targets each two of them are closed to each other. The moving targets are continues from the first frame to the last frame in two state, the first state with no clutter while the other state in more background clutter density. The initial mean $m_0^t = (x, y, \dot{x}, \dot{y})'$ for the initial distribution $p\left(x^t(0)\right)$ is set to m_0^1 = [16.58, 9.3, 0, 0], m_0^2 = [16.37, 9.14, 0, 0], m_0^3 = [11.17, 8.8, 0, 0], m_0^4 = [10.92, 9.08, 0, 0] and covariance p_0^t = diag ([400, 400, 100, 100]), t = *1,2,3,4.* The row and column sizes of the volume (V= $S_W \times S_H$). We initiate the other parameters as: ,V=20x20 , the sampling time Δt = 4 sec , $T = 4 \times 12 = 48$

sec, in addition, we also set the matrices of (1),(2) as $A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$,

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad Q = G\ G', \quad R = \begin{bmatrix} 40 & 0 \\ 0 & 40 \end{bmatrix},$$

$$G = \begin{bmatrix} \frac{\Delta t}{2}^{2} & 0 \\ 0 & \frac{\Delta t}{2}^{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}$$

Given a fixed threshold ($\gamma = 10^{-4}$), we showed that at high signal to noise ratio with no clutter density, the two algorithms appear to perform the tracking of closed spaced moving targets.figure 3(a),(b) shows the NNKF not able to track the closed target correctly where NNDA algorithm associate the track to the false measurement that is related to nearest measurement in the current gate of the predicted target position. figure 3(c) shows the proposed ONNDA algorithm succeed to track the closed target. figure 4(a),(b) show the estimated tracked target position using the NNKF and the proposed ONNDA filters at high SNR as mentioned below . In these figures, the colored solid line represents the underlying truth targets of the trajectory (each target with different color) while the colored + symbol represents trajectory of the tracked targets. The figures show the ONNDA as shown in figure 4 (b) has the ability to track without failing compared to the conventional NNDA as shown in figure 4 (a). The evaluation to tracking with the same scenario is repeated using the two algorithms in heavy clutter density as shown in figure 5(a),(b),(c). The estimated tracked target position in more background clutter is updated correctly using the proposed algorithm that has the advantage to increase the probability of choosing the correct candidate measurement compared to using conventional NNKF as shown in figure 6(a),(b). We also compared root mean square error value (RMSE) for the different two approaches each with four targets at our two cases according to the existing clutter as shown in figure 7(a),(b). In the two cases our proposed algorithm has lower error, RMSE values than NNDA over the frame numbers.

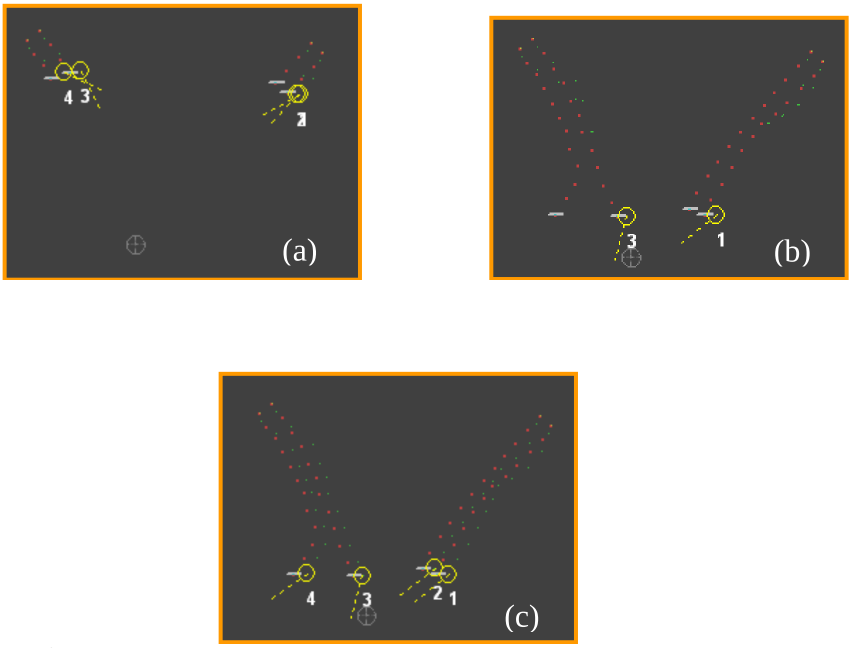
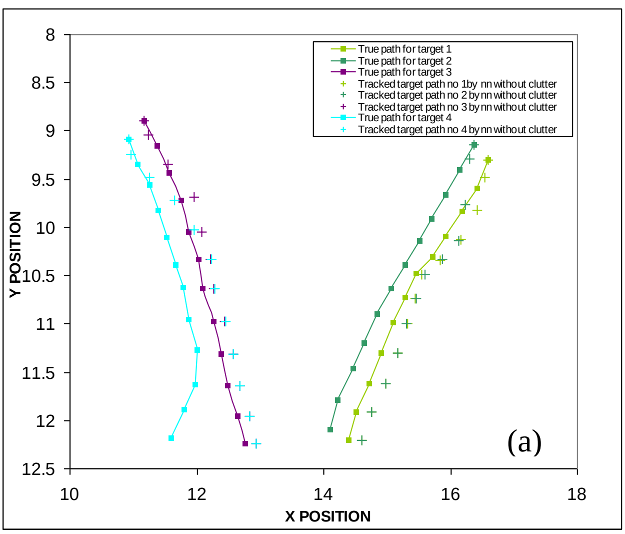


Fig. 3: the state of tracking 4 closed spaced targets move in environment with no clutter density using 2 approaches algorithm NNKF (fail to track the closed target correctly)as in (a),(b), ONNDA (succeed to track the closed target) as in (c)



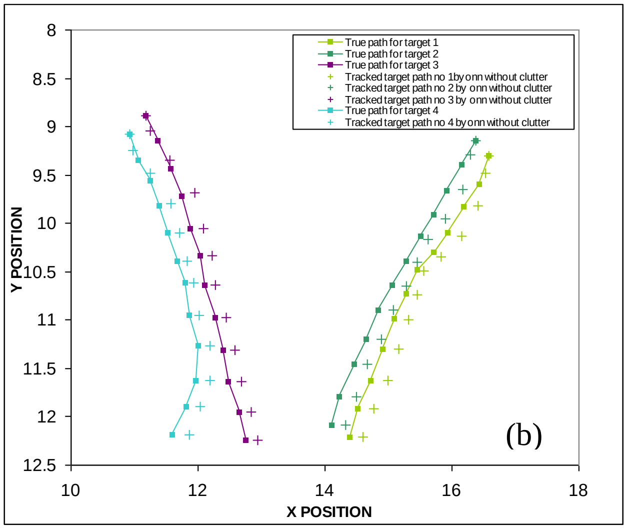


Fig. 4: X- and Y- trajectory show the state of successful tracking to 4 moving closed targets without clutter (4 target with + symbol for tracked target position and solid line for true target path) using 2 algorithms (a) NNKF (b) ONNDA.

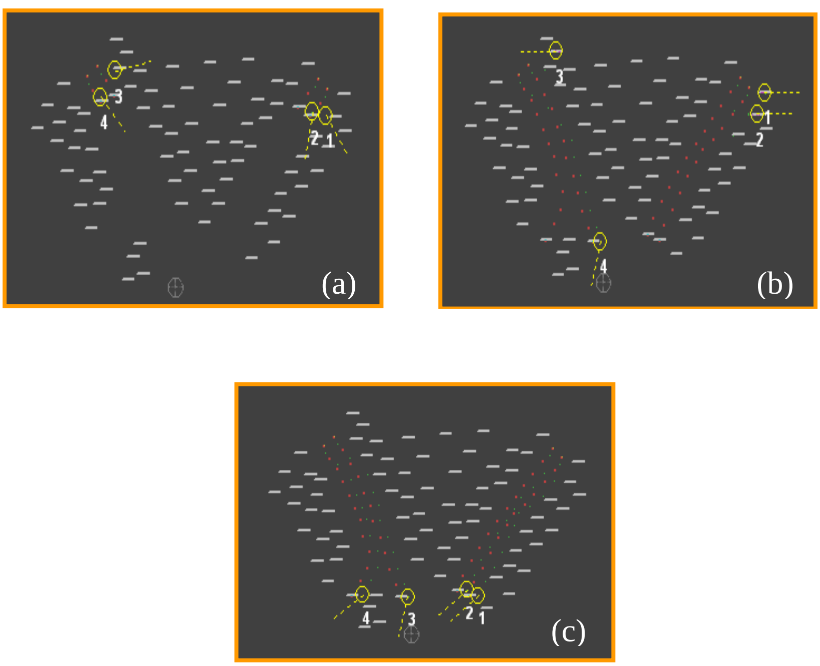


Fig.5: the state of tracking 4 closed spaced targets moving in dense clutter density using 2 approaches algorithm NNKF (fail to track the targets)as in (a),(b), ONNDA (succeed to track all the targets) as in (c).

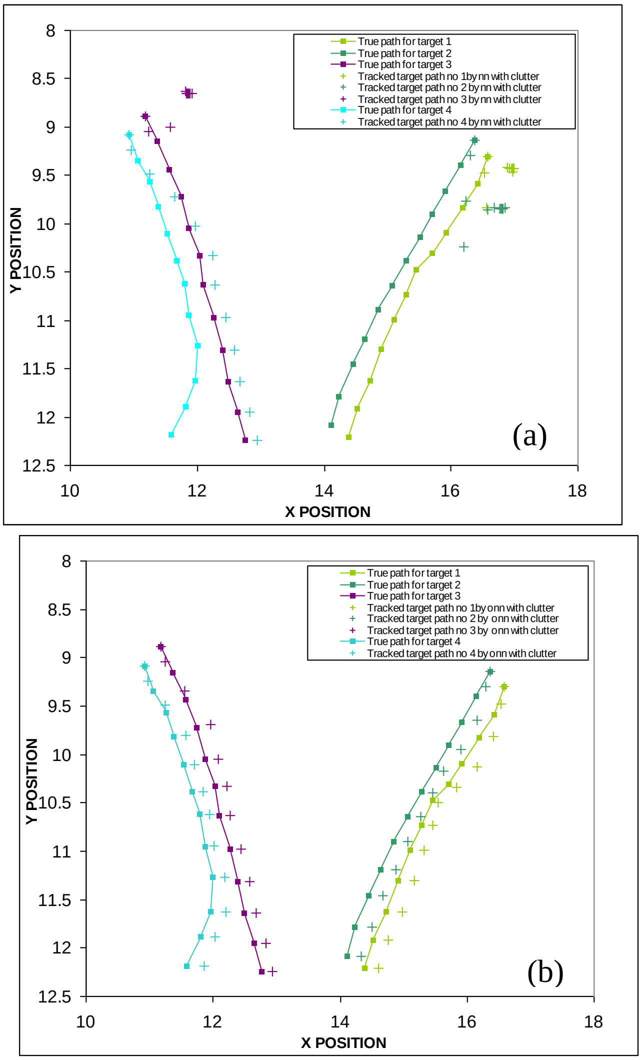


Fig. 6: X- and Y- trajectory show the state of successful tracking to 4 moving closed targets in more background clutter (4 target with + symbol for tracked target position and solid line for true target path) using 2 approaches algorithm (a) NNKF (b) ONNDA.

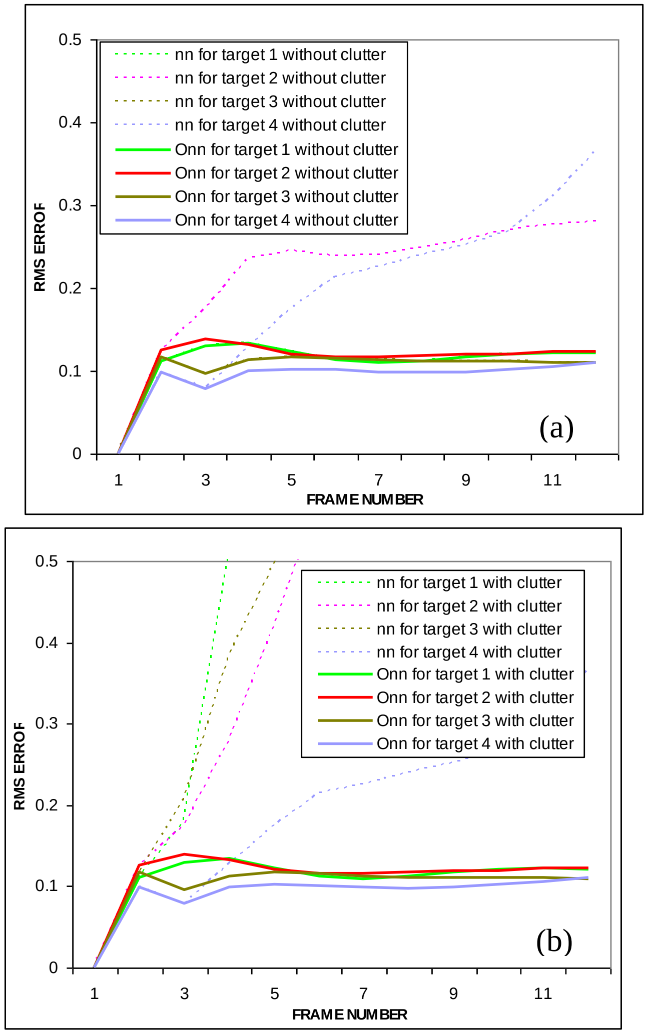


Fig. 7: The root mean square error [RMSE] for each target (4 targets) separately over frame number (each frame take 4 sec / one scan) for the 2 approaches algorithm as (a) with no clutter, (b) with dense clutter. The RMSE is maintained minimum for the proposed ONNDA and less sensitivity to dense clutter.

6. Conclusions

From the results obtained in the simulations for multi-target tracking, it can be seen that the proposed algorithm ONNDA overcome the tracking issues of moving closed spaced targets in dense clutter environment. These issues that lead to loss tracking effectively exists in conventional NNDA algorithm are treated using the proposed algorithm. The proposed algorithm has the ability to detect the false moving targets or clutter to be invalid that are avoided during data association process. Also the proposed algorithm has the ability to continue tracking of closed spaced targets in more background clutter. This approach is more accurate in choosing the correct valid target that depends on last correct position of tracked target instead of predicted target position in calculation of data association process. Thus, we can obtain smaller validated measurement regions with improving the performance of data association Process.

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