Improving Data Association Based on Finding Optimum Innovation Applied to Nearest Neighbor for Multi-Target Tracking in Dense Clutter Environment

E.M.Saad, El.Bardawiny , H.I.ALI and N.M.Shawky

Abstract— In this paper, a new method, named optimum innovation data association (OI-DA), is proposed to give the nearest neighbor data association the ability to track maneuvering multi-target in dense clutter environment. Using the measurements of two successive scan and depending on the basic principle of moving target indicator (MTI) filter, the proposed algorithm avoids measurements in the gate size of predicted target position that are not originated from the target and detects the candidate measurement with the lowest probability of error. The finding of optimum innovation corresponding to the candidate valid measurement increases the data association performance compared to nearest neighbor (NN) filter. Simulation results show the effectiveness and better performance when compared to conventional algorithms as Nearest Neighbor Kaman Filter (NNKF), Joint Probabilistic Data Association Algorithm (JPDA).

***Keywords*—** Data Association, Joint Probabilistic Data Association Algorithm (JPDA), Multi-Target Tracking (MTT), Moving Target Indicator (MTI) Filter, Nearest Neighbor Kaman Filter (NNKF).

I. INTRODUCTION

Multiple-target tracking (MTT) is an essential component of surveillance systems. Real-world sensors; e.g., radar, sonar, and infrared (IR) sensors often report more than one measurement that may be from a given target. These may be either measurements of the desired target or Clutter measurements. Clutter refers to detections or returns from nearby objects, clouds, electromagnetic interference, acoustic anomalies, false alarms, etc. A general formulation of the problem assumes an unknown and varying number of targets that are continuously moving in a given region. The states of these targets and the noisy measurements that are sampled by the sensor at regular time intervals (scan periods) are provided to the tracking system. When tracking a target in clutter, it is possible to have more than one measurement at any time since a measurement may have originated from either the target, clutter, or some other source. It is impossible to associate the target with a measurement perfectly. The performance of a tracking filter, however, relies heavily on the use of the correct measurement. In addition to the detection probability is not perfect and the targets may go undetected at some sampling intervals. A primary task of the MTT system is data association that is responsible for deciding on each scan which of the received multiple measurements that lie in the specified gate size of the predicted target position should update with the existing tracking target. The secondary goal is estimation of the number of targets and their position (states) based on the measurements originating from the targets of interest. In general, data association between measurements and targets is needed, but this is difficult to realize because of measurement error, false alarms, and missed targets. Due to the data association result is crucial for overall tracking process; a gating process is used to reduce the number of candidate measurements to be considered. In data association process, the gating technique [1] in tracking a maneuvering target in clutter is essential to make the subsequent algorithm efficient but it suffers from problems since the gate size itself determines the number of valid included measurements. 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) [2-5], probabilistic data association (PDA) [6,7], joint probabilistic data association (JPDA) [7,8], and multiple hypothesis Tracking (MHT) [9], etc. has been used to track multiple targets by evaluating the measurement to track association probabilities with different methods to find the state estimate [10-12]. NNDA that depends only on choosing

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the nearest valid measurement to the predicted target position, has been used in real work widely because of its low calculation cost, but it readily miss-tracks in dense cluttered environment. PDA, JPDA and MHT need prior knowledge and some of them have large calculation amount [13-16]. We propose here an extended algorithm applied to conventional NNDA to be able to track the multi-target in dense clutter environment. This proposed algorithm is more accurate to choose the true measurement originated from the target with lower probability of error and less sensitivity to false alarm targets in the gate region size than NNDA algorithm. Depending on the basic principle of moving target indicator (MTI) filter used in radar signal processing [16-20] which get rid from the fixed targets and the targets that moving with lower velocity and their moving distance lower than specified certain threshold value, the proposed algorithm reduces the number of candidate measurements in the gate by MTI filtering method that compares the moving distance measure for each measurement in the current gate at the update step to all previous measurement in the same gate at the predicted step and then avoids any measurement in the current gate moves a distance less than the threshold value due to comparison. Thus, decreasing the number of candidate measurements in the current gate lead to decreasing the probability of error in data association process. The main key to detect the moving or fixed false target is the innovation parameter that measure the moving distance between the current measurement and the predicted target position. By calculating this parameter for all measurement in the current gate compared with the scanned previous measurement in the same gate, the optimum innovation of the candidate measurement is obtained. This is called optimum innovation data association (OI-DA) method which is combined with NNDA algorithm to apply the proposed algorithm in multi tracking targets in presence of various clutter densities. Simulation results showed better performance when compared to the two conventional NNKF, JPDA algorithm.

II. Background

A. *Kalman Filter Theory*

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

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

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

Where $x^t(k-1)$ is the *n* x *1* target state vector. This state can include the position and velocity of the target in space $x = (x, y, \dot{x}, \dot{y})'$, The initial target state, $x^t(0)$ for $t = 1,2, \ldots, T$, is assumed to be Gaussian With mean m_0^t and known covariance matrix p_0^t. Where the unobserved signal (hidden states) $\{x^t(k) : k \in N\}, x^t(k) \in X$ be modeled as a Markov process of transition probability $p\left(x^t(k) \mid x^t(k-1)\right)$ and initial distribution $p\left(x^t(0)\right) = N(x^t(0); m_0^t, p_0^t)$. $z^t(k)$ is the *m* **x** 1 measurement vector, $A^t(k-1)$ denotes state transition matrix, $H^t(k)$ denotes measurement matrix, $w^t(k-1)$ and $v^t(k)$ are mutually independent white Gaussian noise with zero mean, and with covariance matrix ***Q***(*k-1*) and ***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

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

and the predicted state mean and covariance is defined as

$$\overline{m}^t(k) = A^t(k)m^t(k-1) \quad \text{and}$$

$$\overline{p}^t(k) = A^t(k)p^t(k-1)A^t(k)' + Q \tag{4}$$

Then, we can update state by

$$m^t(k) = \overline{m}^t(k) + K^t(k)V_{opt}(k) \tag{5}$$

where V_{opt} 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

$$p^t(k) = \overline{p}^t(k) - K^t(k)S^t(K)K^t(k)' \tag{7}$$

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

$$K^t(k) = \overline{p}^t(k) - H^t(K)S^t(K)^{-1} \tag{9}$$

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

$$\left(z_i(k) - H^t(k)\overline{m}^t(k)\right)' S^t(k)^{-1}\left(z_i(k) - H^t(k)\overline{m}^t(k)\right) \le \gamma \tag{10}$$

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.

B. 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 $\hat{z}^t(k \mid k-1)$ and its covariance $S(k)$. When more than one measurement $z_i(k)$ fall inside the gate, the closest one to the prediction is used to update the filter. The metric used is the chi-squared distance:

$$\begin{aligned} D_i^{2\,t} &= \left(V_i^t\right)' S^t(k)^{-1}\left(V_i^t\right) \le \gamma \\ &= \left(z_i(k) - \hat{z}^t(k)\right)' S^t(k)^{-1}\left(z_i(k) - \hat{z}^t(k)\right) \le \gamma \end{aligned} \tag{11}$$

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.

C. 2-D Assignment Algorithm

When multiple targets are present, the nearest neighbor rule can be modified to take target multiplicity into account. Suppose there are T tracks and M validated measurements between them. The single-scan measurement-to-track association problem may be posed as a 2-D assignment problem [23] in which the assignment cost between measurements i and track t is taken as the negative logarithm of:

$$g_i^{2t} = \left|2\pi S^t(k)\right|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2}\left(V_i^t\right)' S^t(k)^{-1}\left(V_i^t\right) \right\} \tag{12}$$

The resulting assignment problem may be solved by the algorithms based on shortest augmenting paths [24]. The algorithm yields associations that enable tracks to be updated with their assigned measurement. Tracks not receiving a measurement are predicted but not updated.

III Optimum Innovation Data Association

The NNKF suffers from tracking in dense clutter environment and its performance is degraded with many loss-tracks accordingly, a new suboptimal algorithm optimum innovation data association (OI-DA) is introduced to increase the tracking performance and to be able to track maneuvering targets in heavy clutter. The main idea based on detecting or distinguishing between the clutter measurements in the gate of the predicted target and the measurement originated from the moving target using two successive scan. The measurements at time $k-1$ that lie in the gate of the predicted target position (predict to time k) is processed by the following method with the measurements at time k that lie in the same gate to obtain the optimum innovation corresponding to distance metric between true target measurement and the predicted target position. To obtain the optimum innovation we have three models that are processed individually, where the NN algorithm is used as one of them. In this section as shown in Fig 1, we introduce a new algorithm.

In the prediction step, Let $Z(k-1) = \{z_1(k-1), z_2(k-1), \ldots, z_{w_n}(k-1)\}$ be a set of points in the 2-D Euclidean space at time $k-1$ where w_n is the number of points at time scan Δt and let $\hat{z}^t(k)$ be a predicted position of the t^{th} tracked target at time k. according to distance metric measure and gate size, let $\bar{Z}^t(k-1) = \{z_1(k-1), \ldots z_i(k-1), \ldots z_{m_i}(k-1)\}$ be a set of the candidate points detected in the t^{th} gate $G_t(k-1)$ of predicted position $\hat{z}^t(k)$ whose elements are a subset from the set $Z(k-1)$ where i =1 to mi (number of detected points in gate $G_t(k-1)$ at time $k-1$) and $\bar{Z}^t(k-1)$ be a set of all valid points $z_i(k-1)$ that satisfy the distance measure condition $\left(z_i(k-1) - \hat{z}^t(k)\right)' S^t(k)^{-1}\left(z_i(k-1) - \hat{z}^t(k)\right) \le \gamma$ for each target t where γ is threshold value that determines the gate size and l =1 to w_n, i =1 to mi, i. e for each target t, 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, let $Z(k) = \{z_1(k), z_2(k), \ldots, z_{w_c}(k)\}$ be a set of points in the 2-D Euclidean space at time k where w_c is the number of points at time scan Δt. The candidate points detected in the same gate $G_t(k)$ as $G_t(k-1)$ of the t^{th} predicted position $\hat{z}^t(k)$ be a subset $\bar{Z}^t(k) = \{z_1(k), \ldots z_j(k), \ldots z_{mj}(k)\}$ from the set $Z(k)$ where j =1 to mj (number of detected points in t^{th} gate at time k) and $\bar{Z}^t(k)$ be a set of all valid points $z_j(k)$ that satisfy the distance measure condition $\left(z_j(k) - \hat{z}^t(k)\right)' S^t(k)^{-1}\left(z_j(k) - \hat{z}^t(k)\right) \le \gamma$ for each target t where l =1 to w_c, j=1 to mj for j=j+1 after each valid point is detected. 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

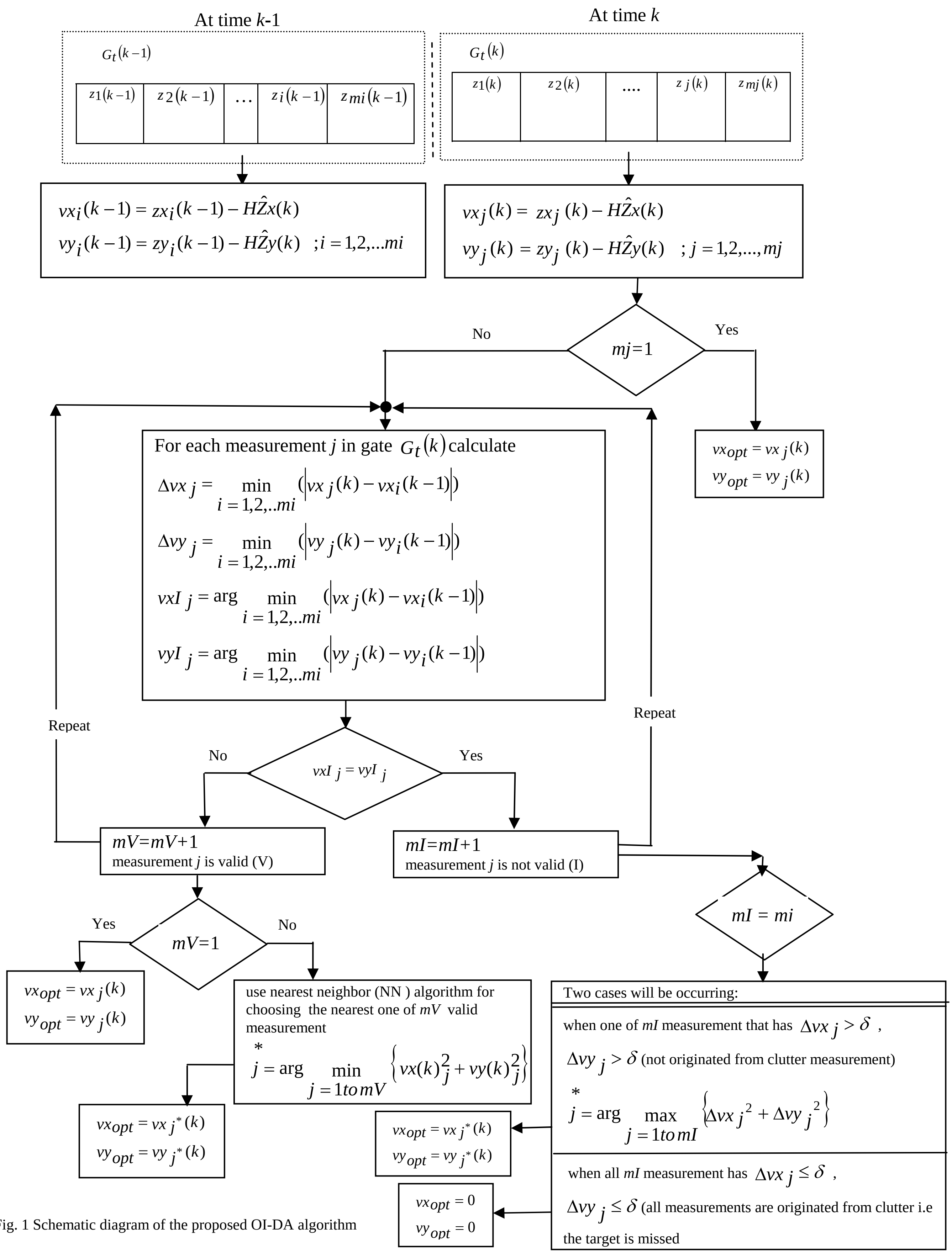

Fig. 1 Schematic diagram of the proposed OI-DA algorithm

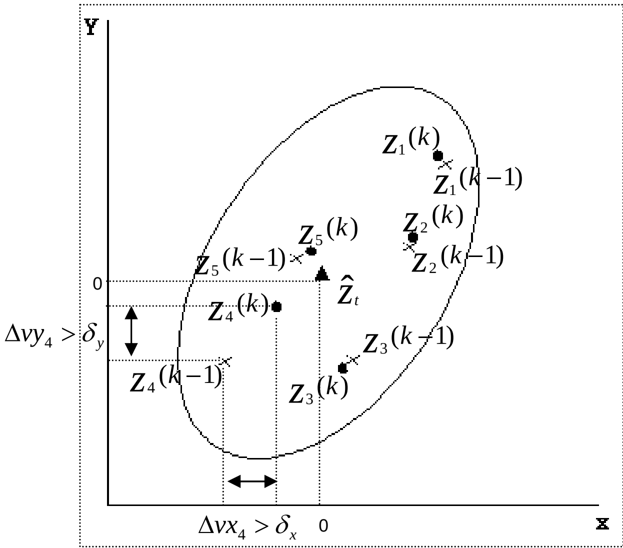

Fig. 2 The current and previous targets position of x,y coordinate in a gate

measurement of x and y component in $G_t(k)$ to its corresponding measurement in $G_t(k-1)$ is calculated and to observe the distance measure between each measurement in $G_t(k)$ and its nearest value. Then we consider that the measurement in $G_t(k)$ is originated from clutter in case its nearest measure not exceed a threshold value which represent fixed or false moving target (clutter). This is based on calculation of the innovation mean for all detected points $z_i(k-1)$, $z_j(k)$ of x and y component as follow;

$$vx_i(k-1) = zx_i(k-1) - H\hat{Z}x(k)$$
$$vy_i(k-1) = zy_i(k-1) - H\hat{Z}y(k) \quad ; i = 1,2,...mi \tag{14}$$

$$vx_j(k) = zx_j(k) - H\hat{Z}x(k)$$
$$vy_j(k) = zy_j(k) - H\hat{Z}y(k) \quad ; j = 1,2,...,mj \tag{15}$$

Each point j in $G_t(k)$ has nearest point i in $G_t(k-1)$ by calculating the minimum absolute difference value $(\Delta vx_j, \Delta vy_j)$ and its index (vxI_j, vyI_j) between the calculated innovation means for all point i at each point j as follow;

$$\Delta vx_j = \min_{i=1,2,..mi} \left(\left|vx_j(k) - vx_i(k-1)\right|\right)$$
$$\Delta vy_j = \min_{i=1,2,..mi} \left(\left|vy_j(k) - vy_i(k-1)\right|\right) \tag{16}$$

$$vxI_j = \arg\min_{i=1,2,..mi} \left(\left|vx_j(k) - vx_i(k-1)\right|\right)$$
$$vyI_j = \arg\min_{i=1,2,..mi} \left(\left|vy_j(k) - vy_i(k-1)\right|\right) \tag{17}$$

Depending on the clutter point has very small change compared to the change in target point of x and y component at two successive scan in each gate its center is the prediction target position. For simplicity, if we assume as shown in Fig.(2), the gate includes 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 , we found that the considering of clutter point has high probability when index vxI_j is the same as or (equal to) vyI_j while the considering of target point has high probability when index vxI_j is different or (not equal to) vyI_j, according to the above consideration we detect how many points mI represent a clutter point (i.e the corresponding measurements j are not valid and are avoided from data association process) and how many point mV represent a target point (i.e corresponding measurements j are valid and one of them has the optimum index that is found by data association process) .The data association process take in consideration the optimum innovation mean (vx_{opt}, vy_{opt}) directly in case that the number of detected points mV is one, which is the normal case when the target exist and the remaining points represent a clutter(invalid points)

$$vx_{opt} = vx_j(k)$$
$$vy_{opt} = vy_j(k) \tag{18}$$

Another case that data association process take in consideration the optimum innovation mean (vx_{opt}, vy_{opt}) directly when existing target with no clutter without entering in calculation model of innovation mean process. i.e. the calculated number of detected point mj is one in $G_t(k)$.

$$vx_{opt} = vx_j(k)$$
$$vy_{opt} = vy_j(k) \qquad \text{, where } j=1$$

Two special cases may be occurring according to the scenario in the following application assignment:-

The first case, gate contain more than one moving target and $mV>1$ as a result of data association process. The optimum innovation mean (vx_{opt}, vy_{opt}) is calculated by NNDA as follow;

$$j^* = \arg\min_{j=1 \, to \, mV} \left\{ vx(k)_j^2 + vy(k)_j^2 \right\} \tag{19}$$

$$vx_{opt} = vx_{j^*}(k)$$
$$vy_{opt} = vy_{j^*}(k) \tag{20}$$

Where j^* is the index of selected measurement from mV valid point that has the minimum distance from the predicted target position.

The second case, all measurements in the gate are calculated to be invalid as result of data association process i.e $mV=0$, $mI = mj$. in this case we have two consideration:-

- The target may be exist and moves small distance when decreasing its velocity due to maneuvering and takes invalid consideration as the remaining false target in the gate but the change in distance is still higher than the threshold value that detect the target as clutter i.e $\Delta vx_j > \delta, \Delta vy_j > \delta$. The optimum innovation mean (vx_{opt}, vy_{opt}) is calculated by selecting the measurement that has the maximum change in distance under condition $\Delta vx_j > \delta, \Delta vy_j > \delta$ as follow,

$$j^* = \arg \max_{j=1 to mI} \left\{ \Delta vx_j^2 + \Delta vy_j^2 \right\} \quad (21)$$

$$vx_{opt} = vx_{j^*}(k)$$

$$vy_{opt} = vy_{j^*}(k)$$

- The target not detected in the gate (missed) and all measurements are considered to be false target. In this case, the updated target is assigned to the predicted target position and no innovation mean value is required i.e

$$vx_{opt} = 0$$
$$vy_{opt} = 0 \quad (22)$$

Finally, we obtain the optimum innovation mean 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 measurement to be invalid (i.e not include in the data association process), this increase the probability for choosing the true measurement originated from the target and improve the data association process.

III. Implementation of Optimum Innovation Data Association (OI-DA) using the Kalman Filter.

We propose an algorithm which depends on the history of observation for one scan and uses innovation mean calculation with a fixed threshold to obtain the optimum innovation mean that is related to the association pairing between the choosing measurement and track (predicted target) and is used in update state estimation of the target. In conventional data association approaches with a fixed threshold, all observations lying inside the reconstructed gate are considered in association. The gate may has a large number of observations due to heavy clutter, this leading to; increasing in association process since the probability of error to associate target-originated measurements may be increased. In our proposed algorithm detecting moving target indicator (MTI) filter is used to provide the possibility to decrease the number of observations in the gate by dividing the state of observations into valid represent moving targets and invalid represent the fixed or false targets that only the valid are considered in association. The proposed OI-DA using Kalman filter is represented in algorithm 1.

Algorithm 1 OI-DA using Kalman filter

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1. for *t = 1 to T* do
2. Do prediction step,

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

where

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

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

3. Calculate optimum innovation mean $V_{opt}(k)$ by OI-DA algorithm described in algorithm 2
4. Do update step

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

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

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

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

5. end for

Algorithm 2 Calculate $V_{opt}(k)$ by OI-DA

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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*:

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

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*

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

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

3. Calculate innovation mean for all measurement lie inside the gate *t* at time *k-1*and *k* respectively

$$vx_i(k-1) = zx_i(k-1) - H\hat{Z}x(k)$$

$$vy_i(k-1) = zy_i(k-1) - H\hat{Z}y(k) \quad ; i = 1,2,...mi$$

$$vx_j(k) = zx_j(k) - H\hat{Z}x(k)$$

$$vy_j(k) = zy_j(k) - H\hat{Z}y(k) \quad ; j = 1,2,...,mj$$

4. if *mj* >1 calculate the index and change of the nearest measurement *i* in the gate *t* at time *k-1* to each measurement *j* in the gate *t* at time *k* for *x* and *y* component.

$$\Delta vx_j = \min_{i=1,2,..mi} (\left| vx_j(k) - vx_i(k-1) \right|)$$

$$\Delta vy_j = \min_{i=1,2,..mi} (\left| vy_j(k) - vy_i(k-1) \right|)$$

$$vxI_j = \arg \min_{i=1,2,..mi} (\left| vx_j(k) - vx_i(k-1) \right|)$$

$$vyI_j = \arg \min_{i=1,2,..mi} (\left| vy_j(k) - vy_i(k-1) \right|)$$

5. Calculate invalid mI measurement (false target) in case $vxI_j = vyI_j$ and mV measurement (true moving target) in case $vxI_j \neq vyI_j$

- Calculate directly the optimum innovation $v_{opt} = (vx_{opt}, vy_{opt})'$ **in case (*mV = 1, j = index(mV)*) *or (mj = 1, j = 1)***

$$vx_{opt} = vx_j(k)$$

$$vy_{opt} = vy_j(k)$$

- Choose NN of ***mV* valid measurement to be** the . optimum innovation $v_{opt} = (vx_{opt}, vy_{opt})'$ **in case (*mV > 1, j = index(mV)*)**

$$j^* = \arg \min_{j=1 to mV} \left\{ vx(k)_j^2 + vy(k)_j^2 \right\}$$

$$vx_{opt} = vx_{j^*}(k)$$

$$vy_{opt} = vy_{j^*}(k)$$

- Choose the measurement **to be** the optimum innovation $v_{opt} = (vx_{opt}, vy_{opt})'$ that has the maximum change in distance under condition $\Delta vx_j > \delta$, $\Delta vy_j > \delta$ in case ***mV* = *0, mI* = *mj, j=index(mI)*** as follow,

$$j^* = \arg \max_{j=1 to mI} \left\{ \Delta vx_j^2 + \Delta vy_j^2 \right\}$$

$$vx_{opt} = vx_{j^*}(k)$$

$$vy_{opt} = vy_{j^*}(k)$$

- Otherwise the above condition, the optimum will be set as

$$vx_{opt} = 0$$

$$vy_{opt} = 0$$

6- end

IV. Simulation Results

Simulation results have been carried out to monitor the performance of the proposed OI-DA algorithm compared to the conventional NNKF and JPDA filter. To highlight the performance of the proposed algorithm, we used a synthetic dataset to track three maneuvering targets which are continues from the first frame to the last frame in varying 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 = [17.7, 9.16, 0, 0], m_0^2 = [13.3, 8.8, 0, 0], m_0^3 = [14.4, 11.7, 0, 0], and covariance p_0^t = diag ([400, 400, 100, 100]), t = *1,2,3*. 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 , $T = 4 \times 32 = 128$ sec, p_D=0.99, in addition,

we also set the matrices of (1),(2) as

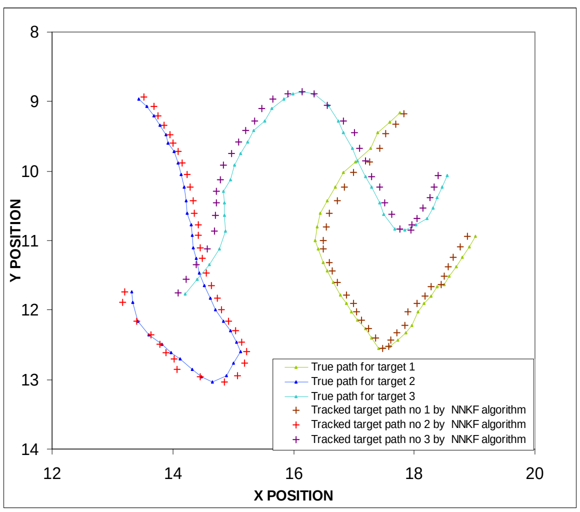
$$A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, Q = G \quad G^T,$$

$$R = \begin{bmatrix} 40 & 0 \\ 0 & 40 \end{bmatrix}, \quad G = \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}$$

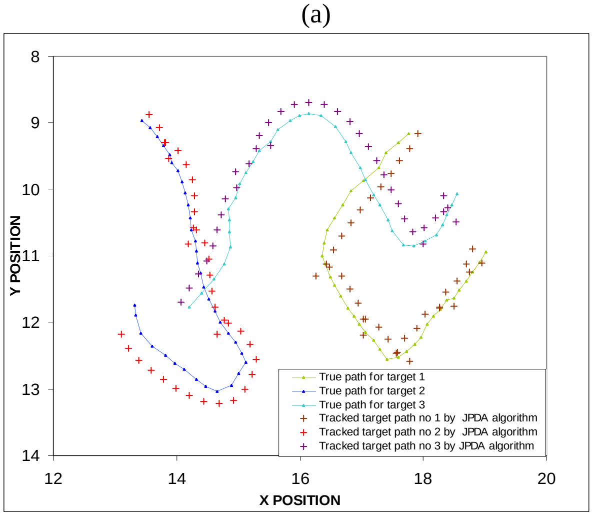
Given a fixed threshold ($\gamma = 10^{-4}$), we showed that at high signal to noise ratio with low clutter density (λ = $0.0005\, m^{-2}$), the three algorithms appear to perform as expected. Fig. 3(a),(b),(c) shows the estimated target tracks using the NNKF, JPDAF and the OI-DA filters respectively at low clutter density. The figures show that the three filters were effectively able to track the targets at high SNR. At low signal to noise ratios the corrupted target track in a uniform clutter with high varying clutter density ($\lambda = 0.001\, m^{-2}$ for medium clutter and $\lambda = 0.01\, m^{-2}$ for dense clutter) is shown in Fig.4, where the NNKF and JPDA filters were not be able to track the targets. Fig. 5,6 show the estimated target tracks using the NNKF, the JPDAF, and the proposed OI-DA filters at the two different SNR as mentioned above where In this 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 shows that only the OI-DA as shown in Fig. 5,6 (c) is able to track the targets at two different heavy clutter density. The explanation of this behavior is due to the fact that, at low SNR the target- originated measurement may fall outside the validation gate when choosing the wrong valid measurements during data association process and as a result, the estimated target states will be clutter- originated. The OI-DA has the advantage to increase the probability of choosing the correct candidate measurement. We also compared error root mean square value (RMSE) for the different three approaches each with three targets at our three cases in different clutter as shown in Fig. 7. Our proposed algorithm has lower error, RMSE values than JPDAF over frame numbers and approximately the same as NNKF.

V. CONCLUSIONS

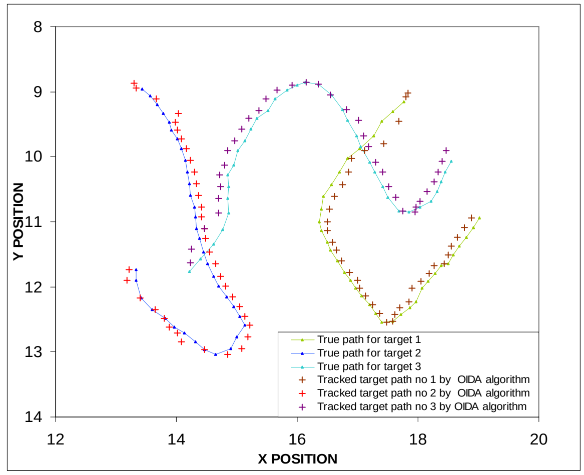
From the results obtained in the simulations for multi-target tracking, it can be seen that at low clutter density (high SNR), all the tracking algorithm (NNKF, JPDAF and OI-DA) are able to track the targets. However, at heavy varying clutter density (low SNR), NNKF and JPDA algorithm fail to track the targets, where the proposed OI-DA algorithm has the capability to maintain the tracked targets. From the valid based measurement regions, The OI-DA algorithm distinguishes between the fixed or false targets to be considered as invalid targets and the moving true targets to be valid during data association process. The OI-DA algorithm overcome the NNKF problem of loss tracking the targets in dense clutter environment and has the advantage of low computational cost over JPDAF. By using this new approach, we can obtain smaller validated measurement regions with improving the performance of data association Process which have been shown to give targets the ability to continue tracking in dense clutter.



(a)

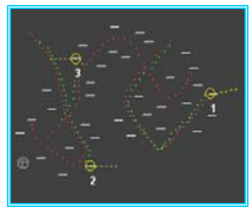


(b)

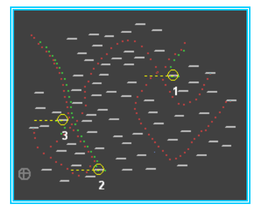


(c)

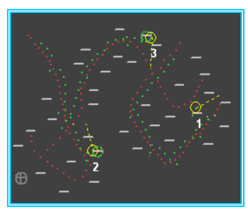
Fig. 3. X- and Y- trajectory show the state of successful tracking to maneuvering multi-targets (3 target with + symbol for tracked target position and solid line for true target path) move in low clutter using 3 approaches algorithm (a) NNKF (b) JPDAF (c) OI-DA.



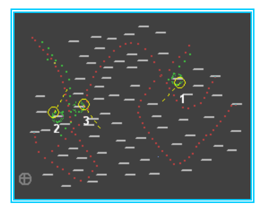
(a)



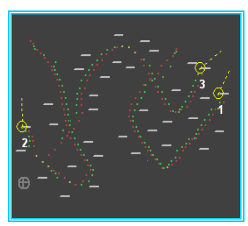
(b)



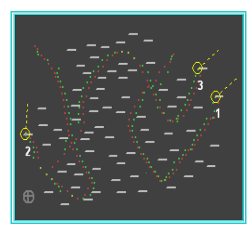
(c)



(d)

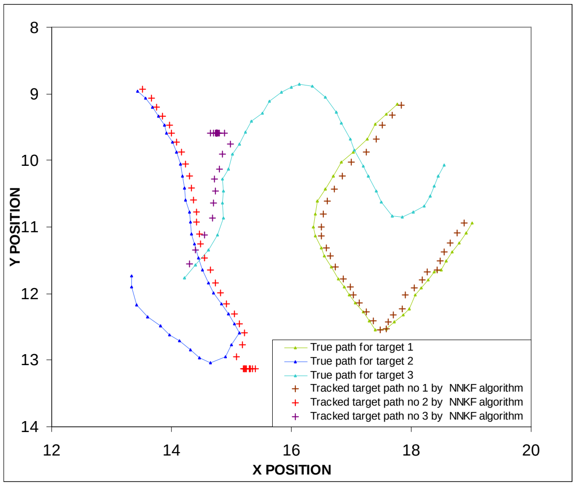


(e)

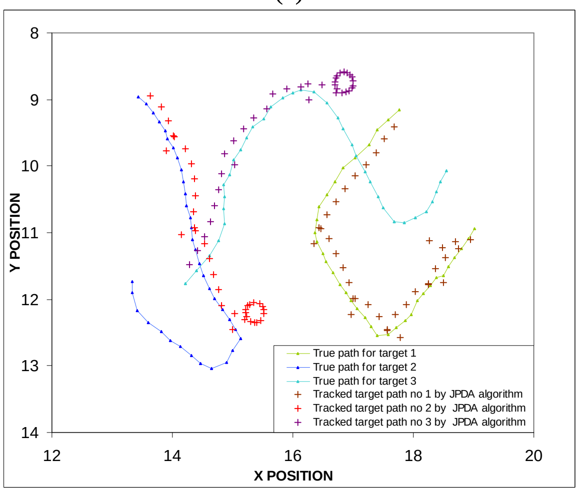


(f)

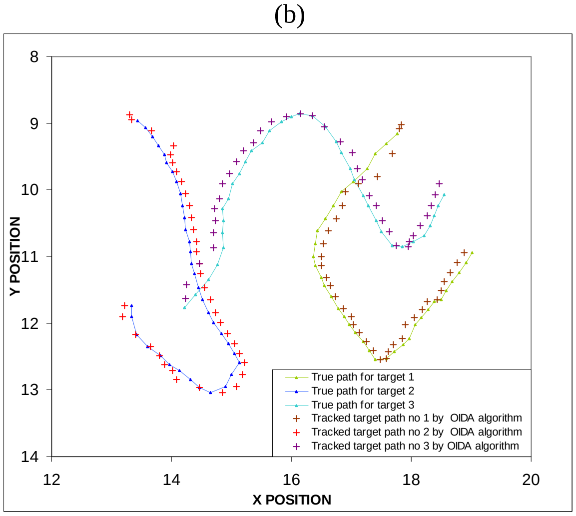
Fig. 4. The state of tracking 3 targets move in different clutter density using 3 approaches algorithm NNKF as in (a),(b), JPDAF as in (c),(d) and OI-DA as in (e),(f). Images (a),(c),(e) show tracking in medium clutter and images (b),(d),(f) show tracking in dense clutter



(a)

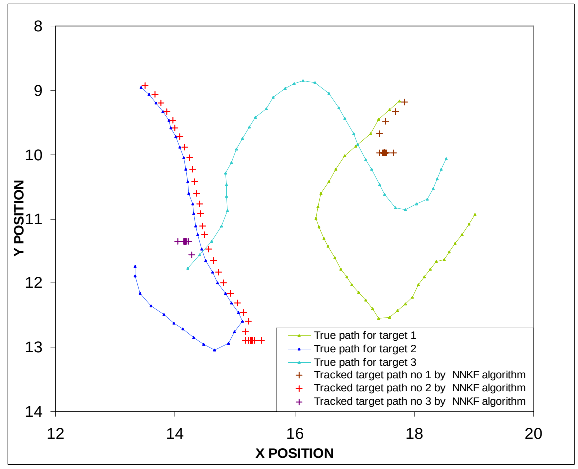


(b)

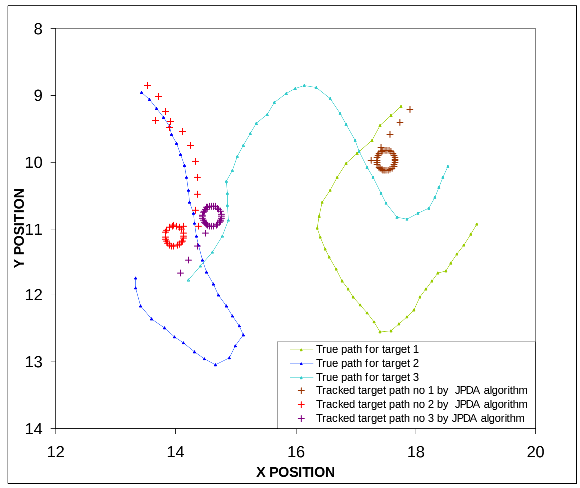


(c)

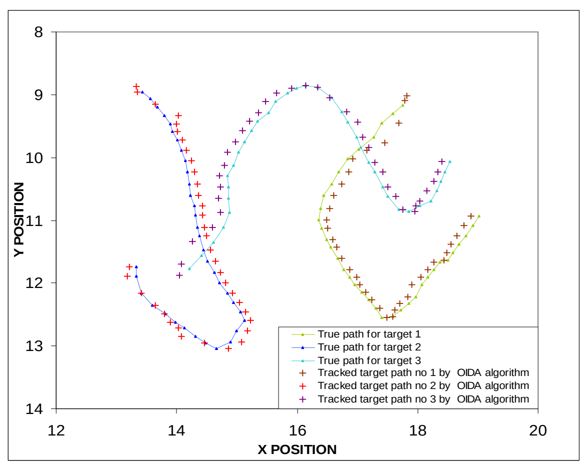
Fig. 5 X- and Y- trajectory show the state of tracking 3 targets in medium clutter (+ symbol refer to tracked target position and solid line to true target path) using 3 approaches algorithm (a) NNKF and (b) JPDAF loss track while (c) OI-DA maintains tracks



(a)

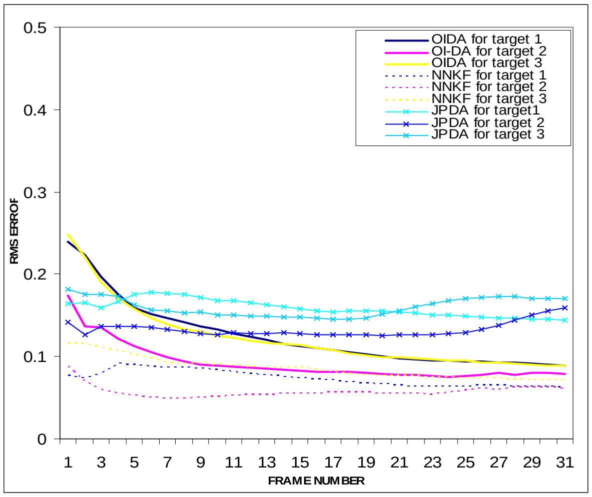


(b)

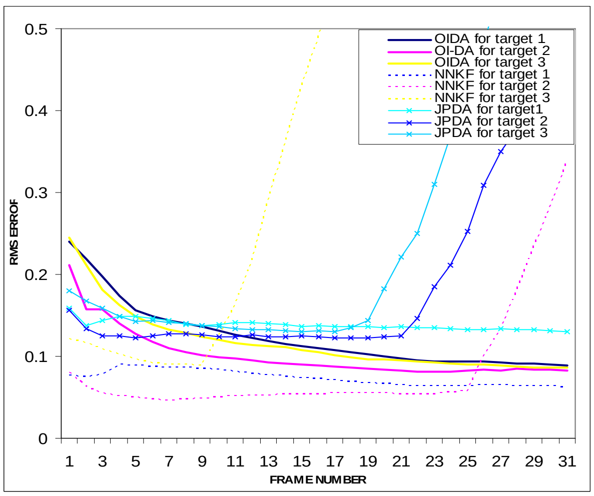


(c)

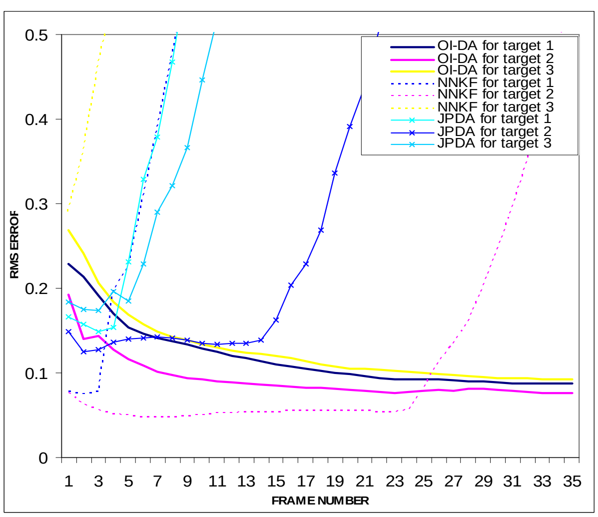
Fig. 6 X- and Y- trajectory show the state of tracking 3 targets in dense clutter (+ symbol and solid line refer to tracked target position and true target path respectively) using 3 approaches algorithm (a) NNKF and (b) JPDAF loss track while (c) OI-DA maintains tracks



(a)



(b)



(c)

Fig. 7 The root mean square error[RMSE] for each target (3 targets) separately over frame number (each frame take 4 sec / one scan) for the 3 approaches algorithm as (a) with low clutter ,(b) with medium clutter and (c) with dense clutter . From (b), (c) the RMSE is maintained minimum for the proposed OI-DA and less sensitivity to dense clutter.

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