Bearing Only Tracking in Cluttered Environment Using Seismic Sensors

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Abstract-This paper presents a study of the problem of tracking a single moving ground target using true seismic data provided by two seismic sensors in cluttered environment. An extended Kalman filter formulated for the bearing-only-tracking applications is used in estimating the target track. Nearest Neighbor (NN) and probabilistic data association filter (PDAF) algorithms are used to solve the data association problem. Results reveal that both algorithms provide almost the same behavior in low and medium clutter densities. In heavy clutter densities PDAF algorithm is much more superior to NN algorithm.

Keywords---- Ground Vehicle Tracking, Extended Kalman Filter (EKF), Bearing-Only Tracking (BOT), Data Association, Clutter measurement.

I. Introduction

Bearing-only-tracking (BOT) is an important branch of tracking systems. The basic problem with BOT tracking systems is to estimate and track the kinematics (position, velocity, acceleration) of a moving target and localize its position using only a sequence of noise-corrupted measurements of the direction of arrival of signal from the target to the sensors. BOT has become a common tracking technique in many important applications. Typical examples are submarine tracking using only noisy measurements provided from one or more passive sonar sensors; aircraft surveillance using radars in the passive mode and the two-dimensional tracking of moving ground vehicles using passive seismic or acoustic sensors.

BOT tracking is known to be a difficult problem, particularly when the angular measurements are extracted from only one single fixed sensor. It is well known [1-4] that if the target is moving with a constant velocity its range cannot be estimated using a single fixed sensor, and its range is said to be unobservable. The target's range will still be unobservable until the senor executes an accelerated motion (or maneuver). At that moment the sensor is described as being 'ownship'. If this does not happen, the tracking system does not have sufficient information to estimate the target range.

Unfortunately, seismic sensors are always fixed in its location. In this study we investigate the problem of tracking a ground target moving with almost a constant velocity with simple maneuvers using two seismic sensors, using the Extended Kalman filter (EKF) [5] which is one of the most widely used in such situations. EKF is a recursive Bayesian estimators which provides a suboptimal estimate in the minimum mean square error (MMSE) sense for tracking problems. However, EKF is known to lack robustness and can diverge against highly-maneuvering targets.

II. Target tracking

A. Tracking in non-clutter environment

The dynamics of a near constant-velocity moving target, formulated in the EKF Cartesian coordinate frame, is expressed as a state vector which includes the position and the velocity of the target in both x-axis and y-axis. At the time step k, the target's dynamics are modeled as

$$\boldsymbol{X}(k) = \boldsymbol{F}.\boldsymbol{X}(k-1) + \boldsymbol{\Gamma}.\boldsymbol{q}(k) \qquad (1)$$

where $\boldsymbol{X}(k) = [x(k)\ y(k)\ \dot{x}(k)\ \dot{y}(k)]^T$ is the target state vector at time step k including the target's position $(x(k), y(k))$ and its velocity $(\dot{x}(k), \dot{y}(k))$ and $\boldsymbol{F}$ is a linear time-invariant state transition matrix that relates the target state at the previous time step $\boldsymbol{X}(k-1)$ to the state at the current time step $\boldsymbol{X}(k)$; where:

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad and \quad \Gamma = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix}$$

where T is the sampling period, and $\mathbf{q}(k)$=[q ; q] is a (2x1) process noise vector in acceleration units (*m/s/s)* which accounts for the deviation of the actual target's motion from the assumed dynamic model. In this study $q = 0.5$ *m/s/s* was used.

The measurement model that relates the azimuth angle $z(k)$ of each of the two sensors to the state vector is described by the highly nonlinear function

$$z^{(i)}(k) = h\left(\frac{x(k)-S^{(i)}(x)}{y(k)-S^{(i)}(y)}\right) \equiv \arctan\left(\frac{x(k)-S^{(i)}(x)}{y(k)-S^{(i)}(y)}\right),$$

and the model of the noisy measured angle for the sensor (i) is defined as

$$z^{(i)}(k) = arctan\left(\frac{x(k)-S^{(i)}(x)}{y(k)-S^{(i)}(y)}\right) + n^{(i)}(k)$$

Where $(S^i(x), S^i(y))$ is the position of the sensor (i), and $n^i(k) \sim N(0, \sigma^2)$ with σ $(in\ radian)$ representing the standard deviation of the assumed Gaussian measurement noise. In this study we used $n^i(k) = 0.5\ radian$

The position of sensor 2 is taken as a reference point such that $(S^{(1)}(x), S^{(1)}(y)) = (0,0)$ while the sensor 1 is located at the coordinate (70,130) meters. It is assumed that both $q(k)$ and $n(k)$ are white, temporally uncorrelated, and zero - mean Gaussian random variables with known covariance $\boldsymbol{Q}(k)$ and $\boldsymbol{R}(k)$ satisfying the following constrains

$E\,[\mathbf{q}(i).\mathbf{q}(j)^T] = \delta_{ij}\boldsymbol{Q}(i)$, $E\,[\mathbf{n}(i).\mathbf{n}(j)^T] = \delta_{ij}\boldsymbol{R}(i)$,
$E\,[w(i).n(j)^T] = 0$ for $\forall i, j$

Under the above assumptions, each iteration of the EKF in BOT applications can be summarized in two steps as follows:

1) Prediction stage: which uses the process model (1) to predict the target state $X(k+1|k)$ from the current state $X(k|k)$ and the process error covariance matrix $P(k+1|k)$ from the current covariance matrix $P(k|k)$:Predicted state:

- $X(k+1|k) = F.X(k|k) + \Gamma.q(k)$
- Covariance matrix of predicted state: $P(k+1|k) = F.P(k,k).F^T + Q$

2) Updating (Correction) stage which uses the current measurement $Z(k+1)$ to update (correct) the predicted target state and its error covariance matrix.

- Compute the innovation vector
  $V(k+1) = Z(k+1) - J_h.\ X(k+1|k)$
  (The difference between the predicted and the received measurement vectors)
- Compute the covariance matrix S of the innovation vector:
  $S = J_h\ P(k+1|k)\ J_h^T + R(k)$
- Compute the Kalman gain:
  $K(k+1) = P(k+1|k)\ J_h^T S^{-1}$
- Update the state vector:
  $X(k+1|k+1) =$
  $X(k+1|k) + K(k+1)\ V(k+1)$
- Update the covariance matrix:
  $P(k+1|k+1) = P(k+1|k) - K\,J_h\,P(k+1|k)$

In BOT, the nonlinear measurement function

$$z^{(i)}(k) = arctan\left(\frac{x(k)-S^{(i)}(x)}{y(k)-S^{(i)}(y)}\right)$$

is linearized about the predicted state x (k+1/k) by using the first-order partial derivatives of the Taylor series expansion of the function arctan (.) and creating the Jacobian matrix defined as:

$J_h(k) = \partial h/\partial x|_{x=x(k+1/k)}$ given in equation (2)

$$J_{h=\partial h/\partial x}|_{x=x(k+1|k)} = \begin{pmatrix} \frac{-\left(y(k)-S^{(1)}(y)\right)}{(x(k)-S^1(x))^2+(y(k)-S^1(y))^2} & \frac{\left(x(k)-S^{(1)}(x)\right)}{(x(k)-S^1(x))^2+(y(k)-S^1(y))^2} & 0 & 0 \\ \frac{-\left(y(k)-S^{(2)}(y)\right)}{(x(k)-S^{(2)}(x))^2+(y(k)-S^{(2)}(y))^2} & \frac{\left(x(k)-S^{(2)}(x)\right)}{(x(k)-S^{(2)}(x))^2+(y(k)-S^{(2)}(y))^2} & 0 & 0 \end{pmatrix} \quad (2)$$

B. Tracking in cluttered environment

The clutter is a type of noise generated mainly as false alarms from the sensor. The clutter spatial density is assumed to be uniform in the case of tracking in cluttered environment. The clutter density (in statistical sense) is defined as the mean number of clutter occurrences per unit area/volume taken from a discrete Poisson distribution every time scan. In the bearing-only-tracking application it is defined as the mean number of clutter occurrences/ unit radian angle/ time scan.

When tracking multiple-targets in the same neighborhood or even tracking a single target in noisy environment the data association problem arises. In such situations the sensor may yield measurements with uncertain origin. One of these uncertain measurements might be selected to update the estimate of the target track. Hence, ambiguities in the association process between the previous known targets and the measurements will always be probable. Degradation in the performance of the estimator would be expected which might lead to a complete loss of the track. Deciding the target from which a received measurement originated is a very crucial issue in multiple-target-tracking systems. This process is known as the data association process. In tracking moving ground vehicles using seismic passive sensors, the sensor receives a significantly low SNR seismic signal due to the high ambient seismic noise level and the wind and temperature effects in the site. Therefore, tracking in such scenarios is more critical than the others. There are several data association techniques used to solve this problem. Extensive publications on the problem of tacking targets in the presence of measurement uncertainty can be found. The nearest-neighbor (NN) techniques [6] are commonly used when tracking either a single or multi targets in low-clutter environments, but their performance degrades in heavy-clutter environments. On the other hand, probabilistic data association filters; (PDAF) [7, 8] are used in tracking a single target in heavy-cluttered environments. These two techniques are presented briefly in the following.

1) Nearest-Neighbor (NN) techniques

In order to isolate some of the clutter measurements, a validation gate is set up centered at the location of the predicted measurement. To guarantee that the true target measurement falls in the gate with some high probability, the dimensions of the gate is determined according to the statistics of the predicted measurement.

When tracking a single target in cluttered environment, a problem arises when more than one measurement fall in the validation gate. The correct measurement and any spurious measurements which exist into the validation gate are considered as validated measurements. Figure (1) shows a typical situation with several validated measurements.

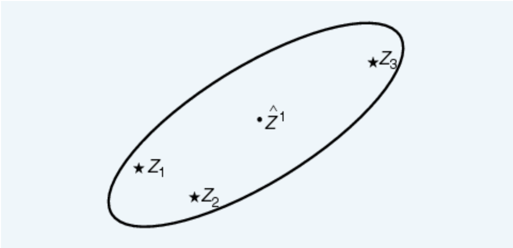

Fig.1, The validation gate centered at the predicted position $\hat{z}_i(k)$ and contains three measurements $z_j, j = 1,2,3$

The two-dimensional region in this figure is an ellipse centered at the predicted position $\hat{z}_i(k)$ of the target at the time step (k). Assuming that the innovation vector $\tilde{z}_{ij}(k)$ between the predicted position $\hat{z}_i(k)$ and the measurement (j) is Gaussian with dimension M, its Gaussian probability density $p(\tilde{z}_{ij}(k))$ is given by s

$$p(\tilde{z}_{ij}(k)) = exp^{-d_{ij}^2(k)/2} / ((2\pi)^{M/2} \cdot \sqrt{|S_i(k)|})$$

$where \quad d_{ij}^2(k) = \tilde{z}_{ij}(k)^T \cdot S_i(k)^{-1} \cdot \tilde{z}_{ij}(k)$, and $|S_i(k)|$ is the determinant of the residual covariance matrix $S_i(k)$.

The value $d_{ij}(k)$ is known as Mahalanobis distance [6] between the predicted position $\hat{z}_i(k)$ and the measurements $z_j; j = 1,2,3$. The measurement having the shortest distance $d_{ij}(k)$ is used to update the estimator.

2) The probabilistic data association filters (PDAF)

PDAF uses *all* the measurements, rather than selecting at each time one of them as in the nearest-neighbor approaches, that might have originated from the target in track Assuming that a set $Z(k)$ of $m(k)$ validated measurements are received at time (k) as

$$Z(k) = \{z(k)_i\}_{i=1}^{i=m(k)}$$

A number of $m(k) + 1$ measurement to track association hypotheses can be formed. The first hypothesis is the case in which all of the measurements fall outside the border of the validation gate. One more measurement-track association hypothesis can be formed for the j^{th} valid measurement ($j = 1, 2, \ldots, m(k)$) inside the gate to be the correct measurement. These hypotheses are exhaustive (include every possible measurement-track association) and exclusive (only one measurement can be correct). The computations of the posterior probabilities of these hypotheses are given as:

The probability $\beta_{i0}(k)$ of the first hypothesis to be true is proportional to:

$$\beta_{i0}(k) \propto (1\text{-}PG*PD)*\lambda^{m(k)}$$

where λ is the clutter density *PD* and *PG* are the probabilities for target detection and gating respectively. Assuming that the innovation vector $\tilde{z}_{ij}(k)$ between the predicted position $\hat{z}_i(k)$ and the measurement (j) is Gaussian with dimension M, its Gaussian probability density $p\left(\tilde{z}_{ij}(k)\right)$, the probability $\beta_{ij}(k)$ that every valid j^{th} measurement $(j = 1, 2, \ldots, m(k))$ to be true is proportional to [6]:

$$\beta_{ij}(k) \propto (PG * PD) * \lambda^{m(k)-1} * \exp^{-d_{ij}^2(k)/2} / \left((2\pi)^{M/2} \cdot \sqrt{|S_i(k)|}\right)$$

where $d_{ij}^2(k) = \tilde{z}_{ij}(k)^T . S_i(k)^{-1} . \tilde{z}_{ij}(k)$

and $|S_i(k)|$ is the determinant of the residual covariance matrix $S_i(k)$.

The probabilities $\beta_{ij}(k)$ of the all $m(k) + 1$ hypotheses is calculated through the normalization:

$$\beta_{ij}(k) = \frac{\beta_{ij}(k)}{\sum_{l=0}^{l=m(k)} \beta_{il}(k)}$$

The next step is to calculate the combined innovation $\tilde{z}_i(k)$ for updating the estimator

$$\tilde{z}_i(k) = \sum_{j=1}^{j=m(k)} \beta_{ij}(k) . \tilde{z}_{ij}(k)$$

where

$$\tilde{z}_{ij}(k) = z_j(k) - J_h . X_i(k|k-1)$$

When computing these probabilities we assumed that the innovation of the correct measurement is normally distributed. This assumption makes PDAF a suboptimal estimator. However, it extends the range of clutter densities range in which targets can be reliably tracked.

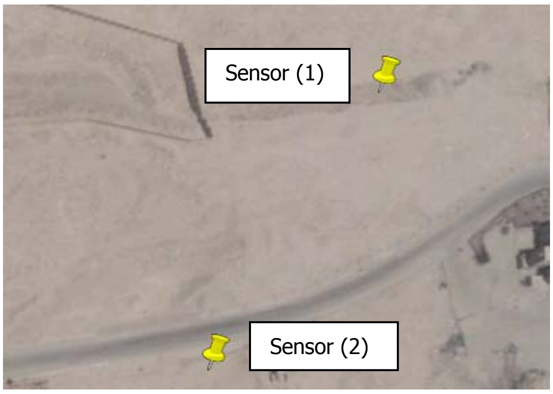

Fig.2: The real target track and the two seismic sensors.

III Field Work

Figure (2) shows the real target track and the position of the two three-component seismic sensors. The location of sensor (2) is assumed the reference point with Cartesian coordinates of (0, 0), while sensor (1) is located at the coordinates (70,130) meters. Each sensor measures the velocities of the ground particles in both East-West and North-South directions. The motion of the ground particles are induced by the seismic waves propagating from the moving target in the direction of the sensor. From the noisy E-W and N-S velocities measured by each of the two sensors, the noisy azimuth angle between the North direction and the line-of-site between the target and the sensor measured in clock-wise direction can be calculated using the measurement model. Figures (3-a and 3-b) show the measured noisy velocities in $(\mu m/sec)$ of the ground particles in both East-West and North-South directions at the location of each sensor, while Fig (4) shows the noisy azimuth angles (in degrees) computed from these velocities for each sensor

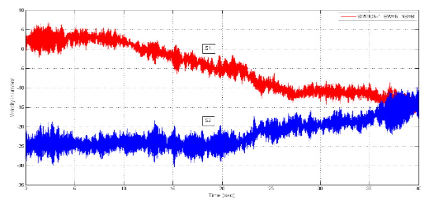

Fig. 3.a, Noisy particle velocities in (m/sec) of sensor (1)

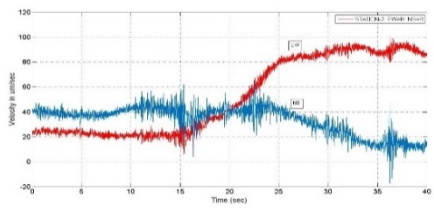

Fig. 3.b, Noisy particle velocities in (m/sec) in sensor (2)

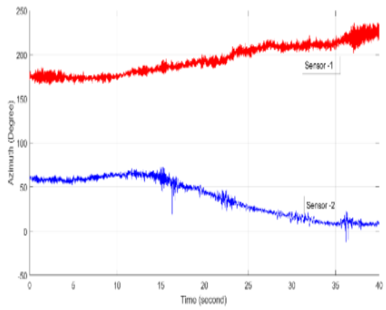

Fig.4, Noisy azimuth angles computed from the measurements of the two sensors

IV. Results and conclusions

In studying the effect of clutter on the behavior of data association techniques in BOT application, we used an EKF supported by the NN and the PDAF techniques in tracking a true ground target moving between two seismic sensors. We used the discrete Poisson distribution to simulate clutter signals with different mean values. The estimated target track at different clutter densities was obtained by a Mont-Carlo simulation of 50 runs.

The estimated track at clean environment (clutter density = 0) was taken as a reference (instead of the actual track which is not known) to obtain an approximate RMS error values between the estimated and the actual target track.

Figures 5 and 6 show that, in non-cluttered environment, both the NN and PDAF techniques provide almost the same estimated target track and the same RMS error in the estimated distance between the moving target and the reference point at senor (2). These results were obtained in the range of mean clutter densities from 0 to 9 clutter ocurrances per radian in each time scan.

Figures 7 and 8 show the estimated distance between the moving target and the location of sensor (2) and the estimated target azimuth measured at the same sensor respectivelty.

Figures 9 and 10 show that the tracking filter with NN failed to track the target at clutter density of 11 clutter ocurrances per radian in each time scan, while the PDAF filter could provide elmost the same performance as in clear environment.

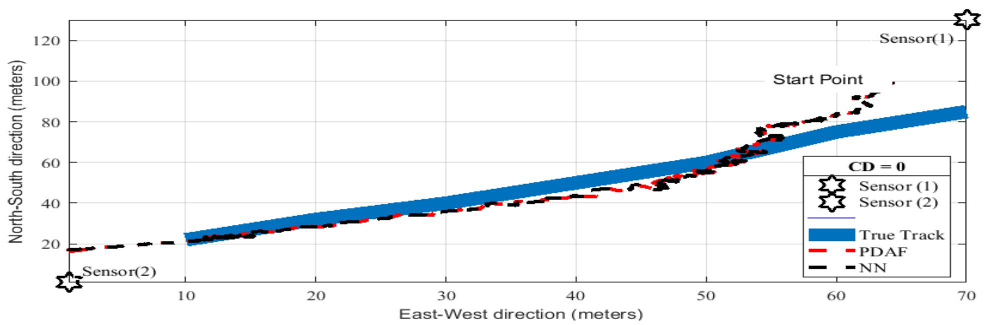

Fig.5, The estimated target track using NN and PDAF in clean environment

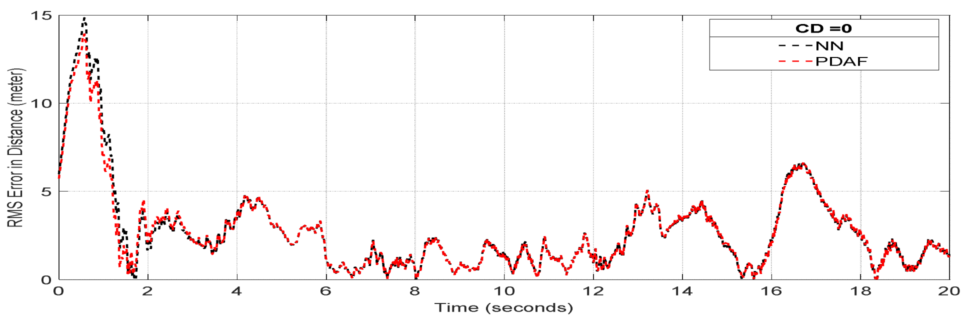

Fig.6, The RMS errors in estimating target distance in clean environment

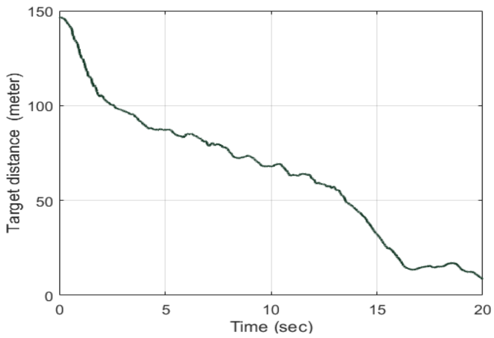

Fig.7, Estimated distance between the target and sensor (2) in clean environment

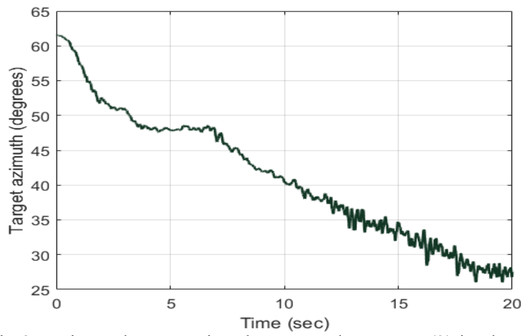

Fig.8, Estimated target azimuth measured at sensor (2) in clean environment

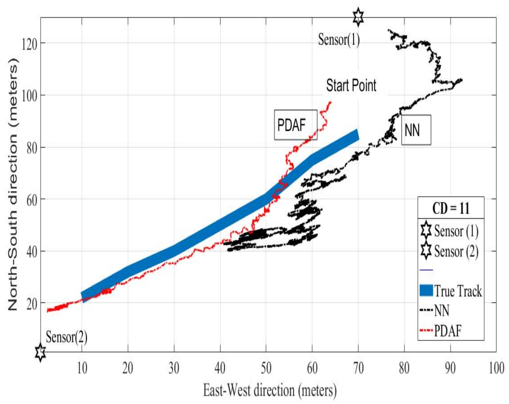

Fig.9, Estimated target tracks at clutter density of CD =11

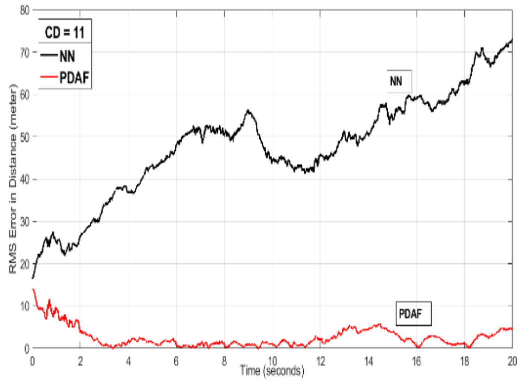

Fig.10, RMS error in estimating target distance at clutter density of CD=11

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