Simple Adaptive Tracking Approach For Nonmaneuvering And Maneuvering Target

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Abstract

This article suggest a simple adaptive approach for tracking the nonmaneuvering and maneuvering target, this tracking approach uses two states per coordinate model to describe the target motion, the residue that provides from this filter is forms the sufficient statistic to detect the existence of maneuver by fading memory detector (FMD) with two-threshold value. When the residue exceeds one on the threshold value, it is used to vary the maneuver noise spectral density (q) in the two states Kalman filter model. This approach is consider as an extended and enhanced for the Castella tracking filter [3] which proposed to track the maneuvering targets for a low data rate track-while-scan (TWS) operation. However, the performance of the suggested approach is tested under different flight environments to compare the effectiveness of it with the performance of the Castella tracking filter.

Keywords: adaptive tracking filter, two state Kalman filter, FMD detection scheme, maneuvering target.

طريقة التتبع التكيفيةِ البسيطةِ للأهدافِ المُنَاوَرَة والغيرالمُنَاوَرَة

الخلاصة

هذه المقالةِ تَقترحُ طريقة تكيفية بسيطة لتتبع للأهدافِ المُنَاوَرَة والغيرالمُنَاوَرَة ، تَستعملُ طريقةِ التتبع هذه مرحلتين لكلّ نموذج منسّق (two state per coordinate model) لوَصْف حركةِ الهدفَ، البقِيّة (residus) التي تُزوّدُ مِنْ هذا المرشِح تشكل الإحصائيات الكافيةُ لإكتِشاف وجودِ المناورةِ بإزالة كاشفِ الذاكرةِ (fading memory detector) بقيمةِ العتبتِين. عندما تَتجاوزُ البقيّة واحد على قيمةِ العتبة، هو يُستَعملُ لتَغيير كثافةِ طيف ضوضاءِ المناورةَ (q) في مرحلتي نموذجَ مرشِحِ كالمان Kalman. هذه الطريقة تَعتبرُ كممتد ومُحَسَّنة لمرشِحِ تتبع كاستيلا [3] الذي إقترحَ لتَعْقيب أهدافِ المُنَاوَرَة لمعدل بيانات منخفضة تُقدّرُ مساراً بينما مَسْحَ (track-while-scan (TWS)). على أية حال، أداء هذه الطريقة المُقترحةِ مُجرّبُ تحت بيئاتِ الطيران المختلفةِ لمُقارنَة فعاليتها بأداءِ مرشِحِ تتبع كاستيلا.

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I. Introduction

The problem of tracking maneuvering targets has received considerable attention due to its obvious importance in a wide variety of military applications, including air defense from missiles and aircraft, air-to-air warfare, naval surface warfare and strategic/theater defense[1].

Maneuvering target tracking refers to the problem of state estimation of the target trajectory subjected to abrupt changes [2].

In radar tracking system, Kalman filter has been successfully applied to target tracking in both nonmaneuvering (constant velocity) and maneuvering conditions such as the simple adaptive tracking filter that suggested by Castella [3] in 1980 to track the maneuvering targets for a low data rate track-while-scan (TWS) operation. This filter consists of two-state Kalman filter, single pole filter and maneuvering detector which continuously estimate the maneuver noise spectral density q in Kalman filter. This has the effect of increasing the tracking filter gains and containing the bias developed by the tracker due to the maneuvering target. Therefore, this filter is heavily filtering when the target is not maneuvering to minimize the effects of noise, and it is lightly filtering when the target is maneuvering in order to reduce the effects of biases.

Variable dimension filter that proposed by Bar-Shalome[4] is another effective tracking approach, where the "fading-memory" average of the innovations is computed based on the lower order state model(when the target is moving at a constant velocity). Once the maneuver is detected, a higher order state model is used and the states estimates in a window are modified. Another adaptive tracker is the state augmentation such as interacting multiple model (IMM) method [5,6,7], where two or more maneuver models are used then the modes will be changed during tracking procedure according to target situations.

In this article, instead of using two or more models, the idea of Castella filter is extended and modified by suggested a simple and effective two state tracking approach for tracking the nonmaneuvering and maneuvering target, this filter use fading memory detector(FMD) to detect the existence of maneuver and a simple designed variable function to estimate the maneuver noise spectral density q in Kalman filter, this approach will called during the contexts as modified Castella tracking filter (MCTF).

The paper is organized as follows. Section II describes the target mathematical model in discrete form. Section III explain in briefly the Castella tracking filter, Section IV present the equations and the operation for the suggested approach, section V present and discuss the results of simulations. Finally section VI gives the conclusion.

II. Target Motion and Observation Model

In target tracking, three decoupled tracking filters can be used with the three independent channels (range, bearing, and elevation) of TWS radar in which each dimension (channel) is characterized by its own kinematics constraints and processes at the same time in independent fashion to supply the state estimates associated with each physical route.

The target and observation models for range, elevation, and azimuth coordinates have similar aspects that are appropriate to define each corresponding tracking filter. Each coordinate has its own dynamic model which is derived suitably to confirm the requirements of implementing the MCTF. Therefore, in this article, we will explain the suggested filter for only single coordinate.

Target motion and the observation (measurement) for range coordinate can be represented by the following discrete-time model with sampling period T[8]:

$$X(k+1) = \Phi X(k) + W(k) \quad \ldots (1)$$

$$Y(k) = HX(k) + V(k) \quad \ldots (2)$$

with,

$$\Phi = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix},\ X(k) = \begin{bmatrix} r(k) \\ v(k) \end{bmatrix},\ H=[1\ \ 0]$$

Where

- Φ : transition matrix
- $X(k)$: the state vector consisting of the radial range and range rate components denoted by $r(k)$ and $v(k)$ respectively.
- $Y(k)$: the observation (the range measurement) from the radar system.
- H : is the observation matrix.
- $W(k)$: is random acceleration process.
- $V(k)$: is the measurement noise.

$W(k)$ is modeled as a white Gaussian noise with zero-mean and covariance matrix $Q(k)$ defined as[10];

$$E\{W(k)W^T(j)\} = Q(k)d(k-j) \ldots (3)$$

where $d(.)$ is the Kroneker-delta function.

The covariance matrix $Q(k)$ is defined by[3],

$$Q(k) = q^T \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \quad \ldots (4)$$

where

$$q = s_m^2 T$$

$$q_{11} = T^2/3$$

$$q_{12} = q_{21} = T/2$$

$$q_{22} = 1$$

where q is the spectral density of the continuous white noise change in acceleration process and s_m^2 is the variance of the change in acceleration noise.

The measurement noise $V(k)$ is modeled as an independent white Gaussian process with,

$$E\{V(k)\} = 0$$

$$E\{V(k)V^T(k)\} = s_r^2 d(k-j)$$

s_r^2 is the variance of the observation channel noise (the error of the measured range). The noise process $W(k)$ & $V(k)$ are uncorrected (i.e. $E\{W(k)V(j)\} = 0$ for all j and k) .

III. Castella Tracking Filter (CTF) in briefly

The CTF consists of two-state Kalman filter, single pole a_R filter and maneuvering detector which continuously estimate the maneuver noise spectral density q as shown in Fig. 1 [3],

The operation of this filter is described as follows [3, 9, 10]:

1) Maneuver is detected separately by monitoring the track residuals (i.e., measured minus predicted values) after appropriate normalization and filtering in a single-pole a_R filter.
2) The magnitude of the output of the single-pole a_R filter z is used to adaptively vary the maneuver spectral density q in the Kalman filter model.
3) When $z \le z_1$, where z_1 is selected as the 95 percent value for a nonmaneuvering target, $q = q_1$. The value of q_1 is selected to achieve the tracking accuracy required for a nonmaneuvering target.
4) When $z = z_2$, where z_2 is selected as the $99\frac{2}{3}$ percent value for a nonmaneuvering target, $q = q_2$. Thus when $z \ge z_2$, there is a high probability that a maneuver is in progress.
5) Between z_1 and z_2 the value of q is determined from the straight line established by two points (z_1, q_1) and points (z_2, q_2).
6) When $z > z_2$, use $q(z) = q_2$ since it is not necessary to increase the filter gains any more than that required to contain the largest maneuver anticipated.

For more details about the selection of q_1, q_2, z_1, and z_2 can be found in [3,9,10];

IV. The Operations and Equations of the Suggested MCTF

The suggested modified Castella tracking filter (MCTF) consists of two-state Kalman filter, maneuvering detector (fading memory detector) with two threshold values which continuously help in modify the maneuver noise spectral density q. The optimal q (which denoted here as q_n) is designed as;

$$q_n(k) = (s_m^{\,2} T) s(k) = q s(k) \quad \ldots (5)$$

Where s (k) is designed variable function that is used for modified the values of q_n. The block diagram of the suggested MCTF for range coordinate is shown in Fig.2,

The recursive two state Kalman filter equations are:

Filter state prediction:

$$\hat{X}(k/k-1) = \Phi \hat{X}(k-1/k-1) \quad \ldots (6)$$

Error covariance prediction:

$$P(k/k-1) = \Phi P(k-1/k-1)\Phi^T + Q(k) \quad \ldots (7)$$

Filter gain:

$$K(k) = P(k/k-1)H^T[HP(k/k-1)H^T + s_r^2]^{-1} \quad \ldots (8)$$

Filter state update:

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)[Y(k) - HX(k/k-1)] \quad \ldots (9)$$

Error covariance update:
$P(k/k) = [I - K(k)H]P(k/k-1)$ …(10)

A simple fading memory average of the innovations from the two state Kalman filter is computed as follows [4]:

$$L(k) = a_F L(k-1) + d(k) \quad \ldots (11)$$

with $0 < a_F < 1$ and

$$d(k) = R^T(k) N^{-1}(k) R(k) \quad \ldots (12)$$

R(*k*) is the "innovation process" of *Y*(*k*),

$$R(k) = Y(k) - H\hat{X}(k/k-1) \quad \ldots (13)$$

Which is zero mean and variance given by;

$$N(k) = HP(k/k-1)H^T + s_r^2 \quad \ldots (14)$$

Since *d*(*k*) is under the Gaussian assumption chi-squared distribution with n_y (dimension of measurement) degrees of freedom. The effective window length (*M*) of the fading memory average over which the presence of a maneuver is [4];

$$M = \frac{1}{1 - a_F} \quad \ldots (15)$$

The procedure of the fading memory detector (FMD) scheme is as follow:

Accept the hypothesis that a maneuver is taking place if *L*(*k*) exceeds a certain threshold which corresponds to 95 percent confidence interval[4].

the variable structure function *s*(*k*) is used to modify the maneuver spectral density q_n of the two-state Kalman filter, we design the variable function *s*(*k*) as ;

$$s(k) = \begin{cases} s_{min} & L(k) \le l_1 \\ L(k) \cdot b & l_1 < L(k) < l_2 \\ s_{max} & L(k) \ge l_2 \end{cases}$$
… (16)

Where s_{min} and s_{max} is the minimum and maximum value for the function *s*(*k*) in respectively, l_1 is the first threshold and l_2 is the second threshold, while b is the thickens between l_1 and l_2. As in [4], the selection of two different threshold levels is done because the innovation sequence of the two state Kalman filter will cross the one threshold level many times, this will lead to disturbing the behavior of the estimator.

The relation between *s*(*k*) and *L*(*k*) is illustrate in Fig.3, also the operation of the *s*(*k*) function with *L*(*k*) is given in Table(1), s_{min} is selected as suitable value that make q_n optimal in Kalman filter to track the target in nonmaneuvering conditions, while s_{max} is selected equal to q_2 which required to contain the largest maneuver anticipated.

V.Simulation Examples

Let us now test the performance of suggested MCTF and compare it with the performance of Castella tracking filter (CTF) using three numerical maneuver scenarios. The track filters parameters for the three scenarios are given by the following:

- Sampling period T=1 *sec*.

-The standard deviation of the observation additive white Gaussian noise s_r = 100 *m*.

-The standard deviation of the plant noise disturbance s_m=5m/sec^2.

-The constant target radial velocity V:300*m*/*sec*.

The value 100 is selected for s_r to examine the filter performance in worst condition, note that the design parameters for the CTF with maximum acceleration 60m/sec^2 are taken from [10], these parameters are:

- a single-pole a_R=0.5.
- b_r=4.8 for 60 m/sec^2 maneuver in the range coordinate.
- The value of q_1=2.16 and the value of q_2=200.
- The value of z_1 = 1.132 and the value of z_2=1.693.
- The initial value of $q = 5$.
- The value of effective window length M=5, (a_F =0.8).

The design parameters for the suggested MCTF are:

- The value $s_{\min} = 1$ and the value of $s_{\max} = 200$.
- The value of $l_1 = 12$, and the value of $l_2 = 17$.
- The thickens value $b_1 = 5$ (the difference between l_1 and l_2).
- The initial value of $q = 5$.

However, estimation of maneuver target range coordinate by these tracking filters require an initial estimates of $\hat{X}(1/1)$ and $P(1/1)$ to be inspired. The initialization is based on the first two observations as follows:

-The two state Kalman is initialized as [9]

$$\hat{r}(1/1) = y(1) \quad \text{and}$$
$$\hat{v}(0/0) = [y(1) - y(0)]/T$$

$$\hat{X}(1/1) = \left|\hat{r}(1/1) \quad \hat{v}(1/1)\right|$$

Where y(0) and y(1) are, respectively, the first and second received sensor measurements.

-The initial error covariance matrix for this coordinate is then [9]

$$P(1/1) = \begin{bmatrix} s_r^2 & s_r^2/T \\ s_r^2/T & 2s_r^2/T^2 \end{bmatrix}$$

The three tested scenarios are:

Scenario#1

in this scenario (example), we assume that target is on a constant course and velocity until time t=120 second, when it maneuvers a slow 90° turn with acceleration input 40 m/sec^2. It completes a turn at t=150 sec, remaining course is constant velocity.

Scenario#2

In this scenario, we assume that the target moves in a plane on constant course with constant velocity until time t=120sec, when it maneuvers a 90° turn with acceleration 30 m/sec^2 and it still with the end of this scenarios.

Scenario#3

This scenario is multi-maneuvering section, we assume that the target moves in a plane on constant course with constant velocity until time t=75 sec, when it maneuvers a 90° turn with acceleration 10 m/sec^2, it completes the turn at t=99 sec, then a second 90° turn stars at t= 100sec with acceleration of 20 m/sec^2 and is completed at t = 150 sec. Then non maneuvering course continuous for 29 sec, followed by the third 90° turn which stars at t=181sec with acceleration of 60 m/sec^2 and it still with the end of this scenarios.

A Monte Carlo simulation of 50 runs was obtained by Eq.(17) for each filters and the roots mean square (rms) values of the range and velocity estimation errors are plotted in Fig.4 for scenarios#1, while the rms range and velocity errors of the second and the third scenarios for the suggested ASKF and CF are shown in Fig.5 &Fig.6 respectively.

$$s_{est}(r) = \frac{1}{N_1}\sum_{k=1}^{N_1}\left\{\left(\frac{1}{N_2}\right)\sum_{i=1}^{N_2}\left[r(k) - \hat{r}(k/k)\right]^2\right\}^{1/2} \quad \ldots (17)$$

where: N_1 is the number of samples for the trajectory.

N_2 is the number of Monte Carlo Runs.

It can be seen from the simulation results that the two filters appear to be equally effective in the constant course of the target trajectories. During the maneuvering period, the suggested MCTF provides a lower rms error than the tracking CTF.

VI. Conclusions

In this paper, we suggest a simple adaptive tracking approach which is consider as a modification and enhancement to the Castella tracking filter(CTF) that proposed to track the maneuvering targets for a low rate track-while-scan (TWS). The modifications are include using the fading memory detector with two threshold values and variable structure function that is used to vary the maneuver noise spectral density (q) in the two states Kalman filter model. The suggested MCTF is simulated under different flight environments,these simulation results illustrate the efficiency of this filter.

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Table (1) the conditions for modify the maneuver noise spectral density (q_n)

The condition on the $L(k)$	$s(k)$ values	The value of $q_n = q \times s(k)$	Maneuver state
If ($L < l_1$) and ($L < l_2$)	$s_{\min}$	$q_n = q \times s_{\min}$	No maneuvering(NM)
If ($L \geq l_1$) and ($L < l_2$)	$L(k)\times b$	$q_n = q \times (L(k) \cdot b)$	Low (LM)or Median maneuvering(MM)
If ($L > l_1$) and ($L \geq l_2$)	$s_{\max}$	$q_n = q \times s_{\max}$	Highly maneuvering(HM)

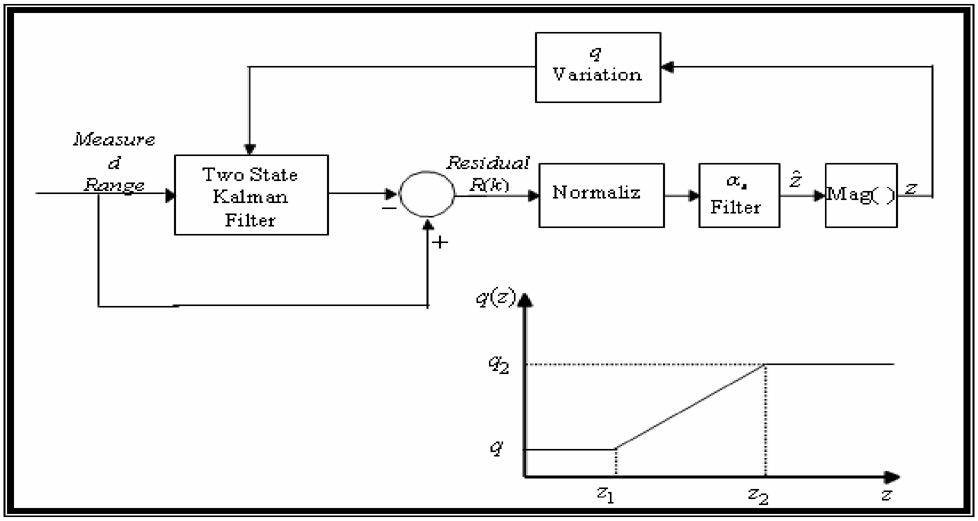

Fig.1: The block diagram of the adaptive CTF for range coordinate.

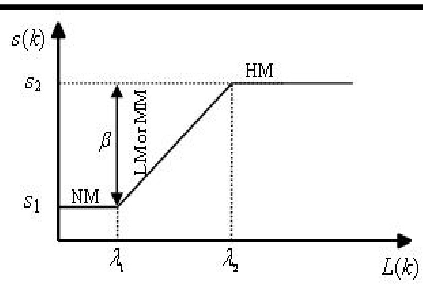

Fig.3: The relation between $L(k)$ and the function $s(k)$.

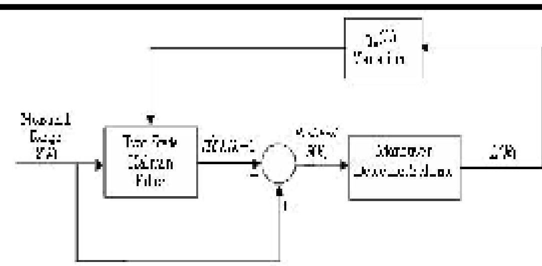

Fig.2: The block diagram of the suggested MCTF for range coordinate.

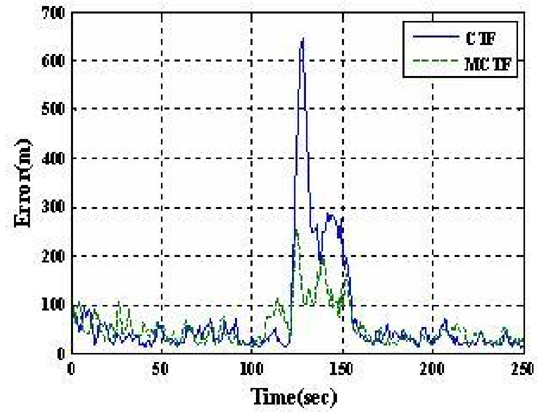

Fig.4a: the rms error of position for scenario#1.

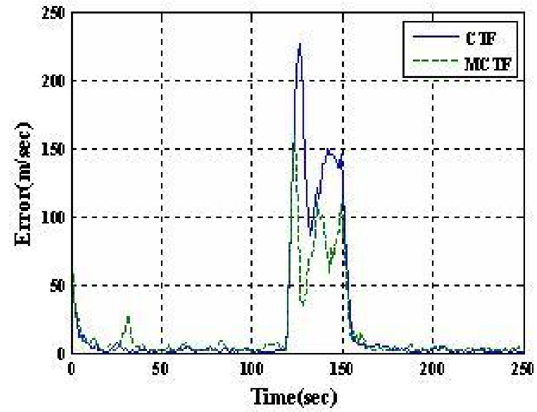

Fig.4b: the rms error of velocity for scenario#1.

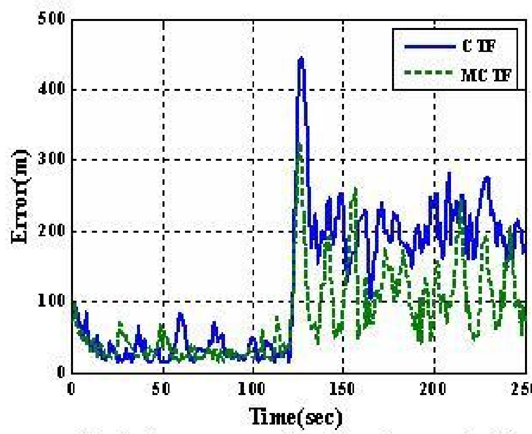

Fig.5a: the rms error of position for scenario#2.

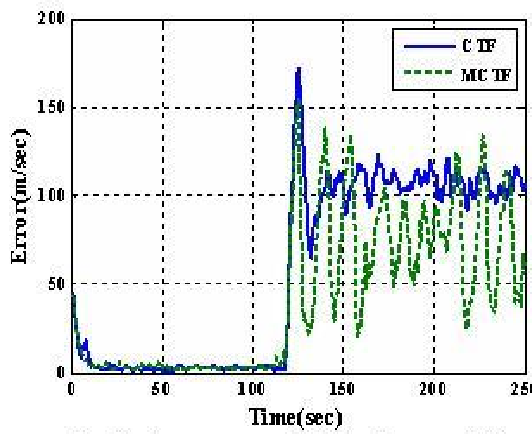

Fig.5b: the rms error of velocity for scenario#2.

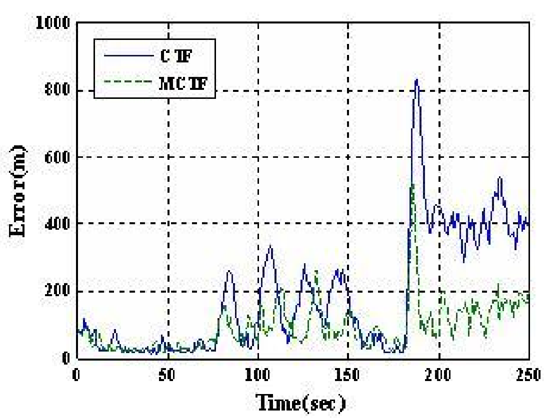

Fig.6a: the rms error of position for scenario#3.

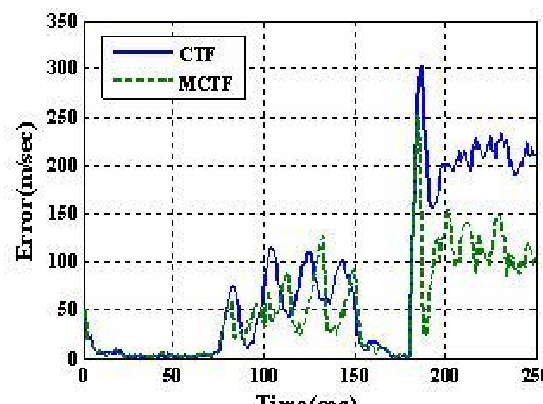

Fig.6b: the rms error of velocity for scenario#3.