Time Variance Constant Gain Dual Extended Kalman Filter Approach to Track Maneuvering Targets

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Abstract: *In this research paper a new technique is recommended for maneuvering target tracking problems in kalman filter. Basically maneuvering targets tracking is very strong area of research with applications in both the military and civilian fields. One of the fundamental problems in visualization is that of maneuver target tracking solve through time variance constant gain dual extended kalman filter (TV-CGDEKF). Within this paper I will make a new approach for design of Kalman filter algorithm to track the target and show the resulting improvement in maneuvering tracking. This is of greatest importance for high-performance real-time applications. More specifically, will describe the technique of how to track Moving of maneuvering. Experimental results demonstrate that, the proposed algorithm is more robust in tracking performance. The proposed method is suitable for indoors as well as outdoors scenes with static background and overcomes the problem of stationary targets fading into the background.*

Keywords: Kalman filter, CGKF, Probability, maneuvering, non-maneuvering, MATLAB.

1. Introduction

The target tracking has been widely applied in military and civil. Many target tracking algorithms are proposed based on so many researches, such as alpha-beta filter, Gaussian sum filter and kalman filter and so on. Although it is convenient for computing, the alpha-beta filter is imprecision Likewise, the Gaussian sum filter is precision, but it is complex to compute ; The kalman filter is used for state estimation with linear dynamic system [2, 3, 9, 13], which can estimate the future state of signal based on the signal statistical characteristic. However, the well-known conventional kalman filter requires an accurate system model and exact prior information, which cannot be directly used to track maneuver target.

2. Maneuver Detection

When the target maneuvers, the control input vector u (k) ≠0, the maneuver term G(k)u(k) would change the target velocities and positions at current time. According to target motion model i.e.

$$x (k+1) = F (k)x (k) + G (k)u (k) + v(k) \qquad\ldots\ldots\ldots 1$$

the target state prediction is

$$\hat{x}(k+1\,|\,k) = F(k)\cdot \hat{x}(k\,|\,k) \qquad\ldots\ldots\ldots\ldots 2$$

But the actual target state prediction in view of the addition with maneuver term G (k)u(k) is

$$\hat{x}(k+1\,|\,k) = F(k)\cdot \hat{x}(k\,|\,k) + G(k)u(k) \qquad\ldots\ldots 3$$

Comparing Eq.2 with Eq.3, we know that the state prediction is changed in one filtering cycle. These changes would cumulate in whole period of target maneuvering, which lead to filtering divergence to large extent. An effective way is to model the maneuver term plus process noise with a new system noise v ′(k) as defined by

$$x(k+1) = F(k)x(k) + v'(k) \qquad\ldots\ldots\ldots\ldots\ldots 4$$

Substituting G(k)u(k)+ v(k) in Eq.1 with the new term v ′(k) , we have the new process equation:

$$x(k+1)=F(k)x(k) \; v'(k) \qquad\ldots\ldots\ldots\ldots\ldots..5$$

where v(k) ~ N (0,Q'$_k$) is the process noise associated ′with term G(k)u(k)+ v(k).

The maneuver detection procedure for the new system equation is based on the normalized innovation squared (NIS), defined as ε_v (k),

$$\varepsilon_v(k) = [z(k) - \hat{z}(k\,|\,k-1)]' S(k)^{-1}[z(k) - \hat{z}(k\,|\,k-1)] \qquad 6$$

where z (k) is the measurement at time instant k , z(k|k-1) is the measurement prediction, z(k) –z(k)-z(k|k-1) is called the measurement residual, also known as the innovation, s(k) is the residual covariance. Under linear Gaussian assumptions, ε_v(k) has a chi-square PDF with n-D degrees of freedom (n is the dimension of the measurement vector),

$$\varepsilon_v(k) \sim \chi^2(n) \qquad\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 7$$

Define

$$\gamma(k,\varepsilon_{max}) = \{z(k): \varepsilon_v(k) \le \varepsilon_{max}\} \qquad\ldots\ldots\ldots\ldots\ldots..8$$

as the probability ellipse in n-D space, according to the nature of χ2 , under the assumption of no maneuvers, the probability of ε_v(k) lower than threshold ε_{max} is

$$P\{\varepsilon_v(k) \le \varepsilon_{max}\} = 1 - \mu \qquad\ldots\ldots\ldots\ldots\ldots\ldots 9$$

where μ is tailed value. Define P$_G$ as threshold probability, we have

$$P_G = P\{z(k) \in \gamma(k,\varepsilon_{max})\} \qquad\ldots\ldots\ldots\ldots\ldots\ldots 10$$

The relationship of these quantities above can be summarized in Table 1.

ε_{max}		1	4	6.6	9	9.2	11.4	16
n_z	1	0.683	0.954	0.99	0.997			0.9999
	2	0.393	0.865		0.989	0.99		0.9997
	3	0.199	0.739		0.971		0.99	0.9989

3. Problem Statement

The measurement origin uncertainty and target (dynamic or/and measurement) model uncertainty are two fundamental problems in maneuvering target tracking in clutter.
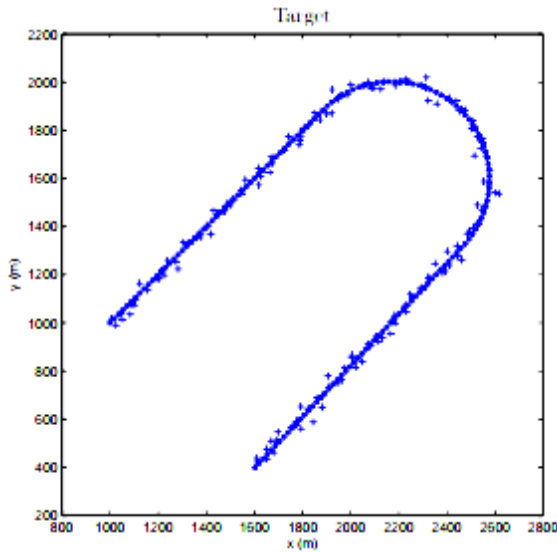
A simple illustration of the maneuver problem with simplistic parameters.
PD = 1.
PG = 1
P_{FA} = 0
KF with CV model
We try different process noise standard deviations σa = 0.1, 1, 10m/s^2.

Maneuvers are the model mismatch problems in target tracking. Using a high order kinematic model that allows versatile tracking is not a solution in the case where data origin uncertainty is present. Instead it makes the gates unnecessarily large and makes filter susceptible to disorder. Hence maneuvers should be detected and compensated. A maneuver should be detected both when the target switches to a higher order model than we use in our TV-CGKF, and when it switches to a lower order model than we use in the TV-CGKF.

4. System Model

Parameterization metric

1.1 Review of geometric-stretch metric
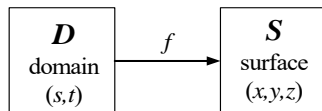
To find a good parameterization f of a given surface S onto a texture domain D, Sander et al.**Error! Reference source not found.** introduce the geometric-stretch metric $E_f(S)$, which is derived as follows.
The Jacobian of the function f is

$$J_f(s,t) = [\partial f/\partial s(s,t) \quad \partial f/\partial t(s,t)] = [f_s(s,t) \quad f_t(s,t)].$$

The singular values Γ and γ of this 3×2 Jacobian matrix represent the largest and smallest length obtained when

mapping unit-length vectors from the texture domain D to the surface S, i.e. the largest and smallest local "stretch".

They are obtained as

$$\Gamma(s,t) = \sqrt{\tfrac{1}{2}\left((a_f + c_f) + \sqrt{(a_f - c_f)^2 + 4b_f^2}\right)} \text{ max sing. value}$$

$$\gamma(s,t) = \sqrt{\tfrac{1}{2}\left((a_f + c_f) - \sqrt{(a_f - c_f)^2 + 4b_f^2}\right)} \text{ min sing. value}$$

where

$$\begin{bmatrix} a_f(s,t) & b_f(s,t) \\ b_f(s,t) & c_f(s,t) \end{bmatrix} = \begin{bmatrix} f_s \cdot f_s & f_s \cdot f_t \\ f_s \cdot f_t & f_t \cdot f_t \end{bmatrix} = J_f^T J_f = M_f(s,t)$$

is called the *metric tensor* of the function f at (s,t). The concept of metric tensor will become important in the derivation of our new signal-stretch metric.

From the singular values Γ and γ, two norms corresponding to average and worst-case local stretch are defined as

$$L_2(s,t) = \sqrt{\tfrac{1}{2}(\Gamma^2 + \gamma^2)} = \sqrt{\tfrac{1}{2}(a_f + c_f)} \text{ and } L_\infty(s,t) = \Gamma.$$

The L_2 stretch norm can also be expressed using the *trace* of the metric tensor as $L_2(s,t) = \sqrt{\tfrac{1}{2}\text{tr}(M_f)}$.

The squared L_2 stretch norm is integrated over the surface S to obtain the geometric-stretch metric

$$E_f(S) = \iint_{(s,t) \in D} (L_2(s,t))^2 \, dA_S(s,t),$$

where $dA_S(s,t) = ||M_f(s,t)| \, ds \, dt$
is differential surface area.

In our setting where the surface S is a triangle mesh, f is piecewise linear and thus its Jacobian J_f is constant over each triangle. Therefore the integrated metric can be rewritten as a finite sum:

$$E_f(S) = \sum_{\Delta_i \in D} \left(\tfrac{1}{2}\text{tr}\left(M_f(s_i, t_i)\right) A_S(\Delta_i)\right),$$

where $A_S(\Delta_i)$ is the surface area of triangle Δ_i, and $M_f(s_i, t_i)$ is the (constant) value of the metric tensor at any point $(s_i, t_i) \in \Delta_i$.

5. Proposed Implementation

TV-CGDEKF (Time Variance- Constant Gain Dual Extended Kalman Filter)
- A novel approach to tracking a maneuvering target is developed. This approach does not rely on a statistical description of the maneuver as a random process. Instead, the state model for the target is changed by introducing extra state components when a maneuver is detected.
- The maneuver, modeled as acceleration, is estimated recursively. The performance of this estimator is shown to be superior to a recent algorithm presented by Chan et al. that handles the maneuver by estimating it as an unknown input.
- A significant departure from the current practice of comparison of algorithms is made: a recently introduced rigorous statistical methodology is used in the comparison of these estimators.

- An enhancement of the variable dimension (VD) filter for maneuvering-target tracking is presented. The use of measurement concatenation, a procedure whereby fast sampled measurements are stacked while maintaining their proper relationships with the states, leads to significant reduction in estimation error by low processing rate algorithms.
- The use of double decision logic (DDL) for the maneuver onset and ending detection as well as appropriate procedures for initialization of the estimation filters results in improved maneuver detection and filter adaptation. Simulation results show the performance of the proposed enhanced variable dimension (EVD) filter.

The operation of the two stages EKF is described as follows. The first stage is the same as general EKF. Once a maneuver is detected at time instant, the normal process noise is substituted with the new one. On the contrary, when the termination of the maneuver is detected, the process noise is reset to normal instance, the filtering process go from the second stage to the first stage. One cycle of the maneuvering target tracking algorithm is shown in Figure 1.
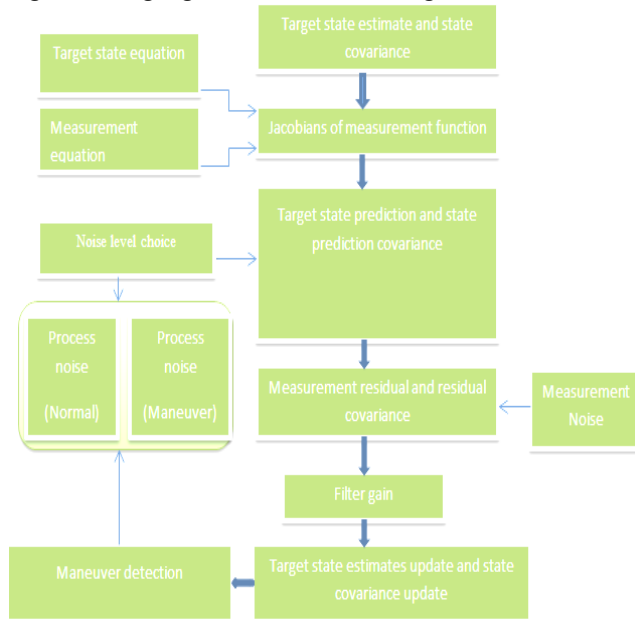

Figure 1: Proposed approach for maneuvering target tracking

6. Result

The use of Jacobian approach is actually a back propagate approach to minimize the estimation error in terms of sum of square. This approach can be applied to general nonlinear optimization.
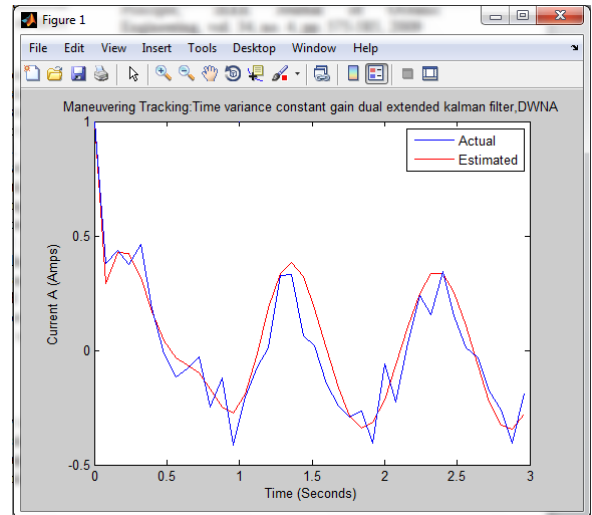

Figure 2: Maneuvering Tracking Improved Actual and Estimated For TVCGDEKF, DWNA

The deals with some variants of the discrete white noise acceleration Kalman filter which prove useful when some of the assumptions of the conventional Kalman filter break down.

In above result figure the actual parameter is better than estimated. In a DWNA state model the result must be verified in practical environment.

In order to illustrate the CGKF for state-estimation, we provide a new application example corresponding to noisy time-series estimation
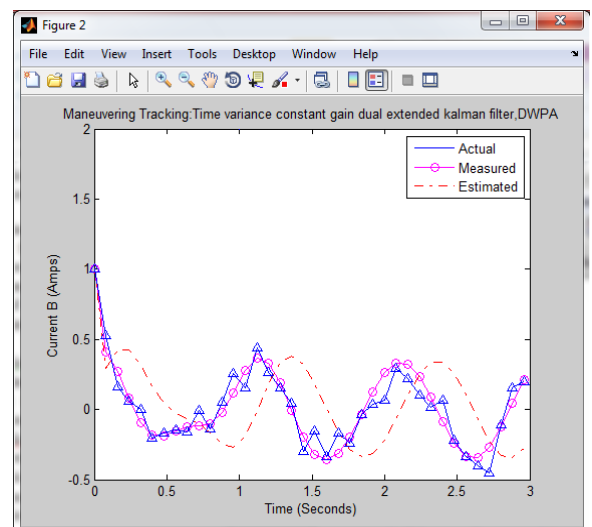

Figure 3: Maneuvering Tracking Improved Actual, measured and Estimated for TVCGDEKF, DWPA with respect to Current
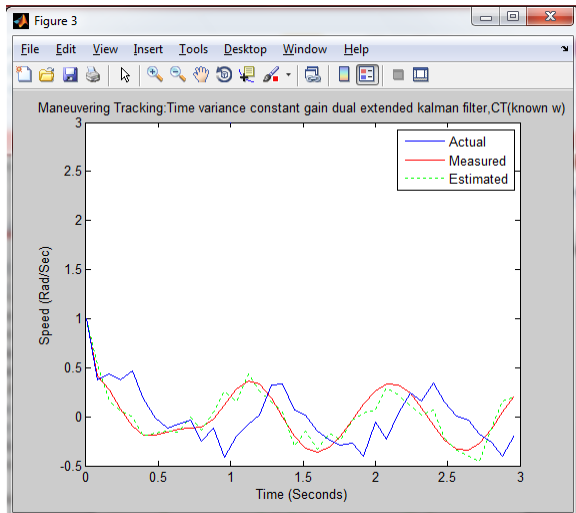
Figure 4: Maneuvering Tracking Improved Actual measured and Estimated for TVCGDEKF, CT (known w) with respect to Speed

In above figure we present results for the TVCGDEKF, CT (known w) with respect to Speed. Development of an Unscented Smoother for a standard estimated approach. As in the prior state-estimation example, we utilize a noisy time-series application modeled with neural square root for illustration of the approaches
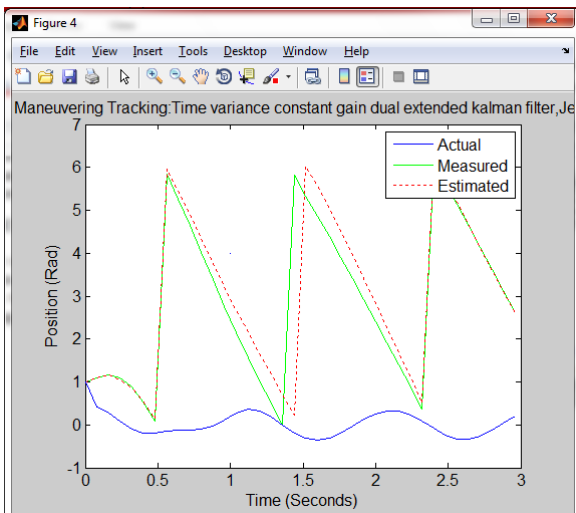

Figure 5.4: Maneuvering Tracking Improved Actual measured and Estimated for TVCGDEKF, JERK with respect to Position

In the TV-CGDEKF, JERK with respect to Speed a separate state-space representation is used for the Time and the Position.
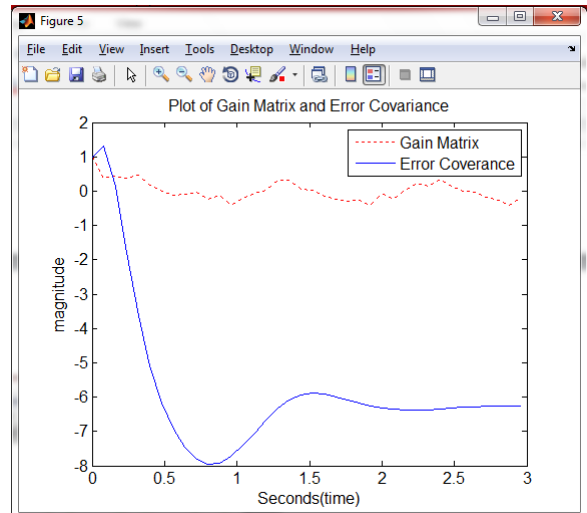

Figure 5: Maneuvering Tracking plot gain matrix and error covariance for TVCGDEKF, JERK with respect to magnitude

As part of the TV-CGDEKF algorithm, we implemented the TVCGDEKF for Time estimation. This represents a new parameter estimation technique that can be applied to such problems as training Gain Matrix for either regression or classification problems.

7. Conclusion

We have investigated the use of the TV-CGDEKF algorithm in the setting of maneuvering targets tracking. First, we considered application to targets that switch in linear Gaussian assumptions. Second, we presented experiments where the TV-CGDEKF uses multiple models on the state of the filter rather than on the state of the target. An algorithm (i.e. TV-CDGKF) combining multiple model method based on Jacobian approach is proposed in this work to address the problem of existing maneuvering target tracking in military andcivilian domains. Multiple model method well-known methods to cope with the target model uncertainty and measurement origin uncertainty, respectively. Existing methods combined these two algorithms CGKF and EKF, where the number of hypotheses in MHT and the number of model trajectories in MM are reduced separately.

Furthermore, this work only deals with maneuvering target tracking. A future direction will be to investigate multi target tracking. The algorithms of future have to be intelligent and thus adopt a new way of working.

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