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On the divergence of information filter for multi sensors fusion

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ABSTRACT

The paper deals with the divergence of information filter in multi sensor target tracking problem using bearing only measurements. Information filter has a number of advantages in terms of computational requirements over Kalman filter for target tracking applications. Compared to Kalman filter it also has the advantage that one can start estimation even without an initial estimate. But this filter is seen to diverge after tracking for a short period of time, even when the target is moving at a constant velocity. A technique to overcome this problem has been discussed in this paper. The information update equations of the conventional information filter are modified in terms of fuzzy function of error and change of error, and the results have been found to be encouraging. The efficacy of the technique in preventing divergence is demonstrated in the context of tracking a maneuvering target also.

1. Introduction

The processes of inferring a value of a quantity of interest from indirect, inaccurate, and uncertain observations is called estimation [1]. This paper deals with estimating the state of a moving target, namely its position and velocity from the measurement of the instantaneous bearings received from 4 stable sensors. The relevant literature is rich with a number of efficient techniques for target tracking applications [2]. The target tracking problem can be considered as a linear filtering problem and a recursive solution to the discrete data linear filtering problem is a famous paper by Kalman in 1960 [1,3]. Since its publication, Kalman filter has been the subject of extensive research and application, especially in the areas of autonomous or assisted navigation. This filter efficiently estimates the state of the target in a way that minimizes the mean squared error between the measurement and estimate. Multi sensor target tracking is seen to be advantageous over single sensor target tracking [4,5]. The information filter is a modified version of Kalman filter, where in a recursive computation of the inverse of the covariance matrix is carried out. It has been shown to be less demanding computationally for systems, where dimension of the measurement vector is larger than that of the state [6,7]. Compared to Kalman filter, it also has the advantage that one can start estimation even without an initial estimate, there by implying that one can start the estimation with initial information matrix, the inverse of covariance matrix, $P(0/0)^{-1}$ as 0. This results in a non informative prior, because of infinite uncertainty associated with it.

The present work reports the information filter, which demonstrates a bearing only tracking problem, using measurements received from 4 stable sensors (like the ground stations), where the target was assumed to move with a constant velocity. The paper also reports the tracking of a maneuvering target. Each sensor was assumed to be autonomous and has sufficient computational power to estimate the information about the states. The information measures computed by each sensor is communicated to all other sensors for estimating the state of the target [6,7].

Though the filter demonstrated fast convergence, as was reported in literature [6], it was observed that the filter begins to diverge after tracking for a short time. It was seen that the innovation or tracking error diverges gradually during the tracking. The present work, demonstrates a fuzzy technique to control this divergence. The seven fuzzy logic functions used here generate the linguistic terms corresponding to the numerical values of error and rate of change of error. The inferencing process generates the correction to be applied to the measurement error co-variance, which in turn helps to control the divergence. The results were found to be encouraging in terms of mean square error in position and stability in velocity. It is also seen that the resulting algorithm for fusion of information leads to better performance even during a target maneuver.

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2. Process and observation model

The target state is assumed to be a 4 dimensional vector representing x and y position of the target and the velocities in the x and y directions.

The state vector at any time k is defined as

$$X(k) = [x(k), y(k), v_x(k), v_y(k)]^T$$

where $x(k)$, $y(k)$, $v_x(k)$, $v_y(k)$ are the x position, y position, x velocity, y velocity respectively at time k. It is assumed that the target follows a uniform velocity model, and the state evolves in time according to

$$X(k+1) = A \cdot X(k) + G \cdot \omega(k) \tag{1}$$

where 'A' represents the process transition matrix (for constant velocity model) and 'G' the process noise gain matrix and are given by

$$A = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad G = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix}$$

where T is the sampling time. $\omega(k)$ is the process noise with 0 mean and covariance 'Q'. The bearing angle measurements at any time k, are given by $Z_i(k)$ where i = 1, 2 3, 4 corresponding to the 4 sensors. The sensors observe the target according to the non linear observation model given by

$$Z(k) = h(k, X(k)) + v(k) \tag{2}$$

where 'h' is the measurement function that relates the bearing angle and the target state and $v(k)$ the associated observation noise that is taken as uncorrelated white sequence. The measurement error co-variance, R and the co-variance of the plant, Q are given by

$$R = E[v(k)v(k)^T] \tag{3}$$

$$Q = E[\omega(k)\omega(k)^T] \tag{4}$$

3. Fuzzy logic based information fusion

The problem of divergence of the information filter, tracking based on the observation of relative bearing angles only, is considered in the present work. The filter shows a tendency to diverge after an initial convergence, on account of limited observability. A decision making strategy based on Fuzzy logic is proposed in the present work to alleviate the problem of divergence. A decision function computed on the Fuzzy variables corresponding to the error and the change in error is used to correct the measurement co-variance, used in the filter equation. The fuzzy logic uses the error and rate of change of error in bearing angle as linguistic variables [8]. The theory of fuzzy logic controllers and how fuzzy logic can be used to control divergence in Kalman filters has been referred from literature [9,10]. The seven fuzzy variables are defined on each of the two variables viz. error.

$$e = Z(k) - Z'(k) \tag{5}$$

where $Z'(k)$ is the predicted bearing measurements from the estimates and change of error

$$\Delta e = \frac{e(k) - e(k-1)}{T}, \quad \text{where } T \text{ is the sampling interval} \tag{6}$$

The total support for e and Δe of bearing angle is from −1 to +1. All membership functions of the fuzzy set are represented as a Gaussian function with center 'c_i' and variance 'σ_i^2' for error 'Δe' and c_j and σ_j^2 respectively for change of error Δe such that, $-1 \leqslant c_i, c_j \leqslant +1$ and $\sigma_i, \sigma_j = 2$ for Case 1 and $\sigma_i = 1$, $\sigma_j = 3$ for Case 2 and Case 3, in order to allow sufficient overlap in the fuzzy terms.

The membership functions are given by

$$\mu_i(e) = e^{\frac{-(e-c_i)^2}{2\sigma_i^2}} \tag{7}$$

$$\mu_j(\Delta e) = e^{\frac{-(\Delta e-c_j)^2}{2\sigma_j^2}} \tag{8}$$

where i and j varies from 1 to 7 to define 7 fuzzy variables each for e and Δe.

The definition of fuzzy variables is given in Table 1, below by uniformly spreading the support of each variable over the range of e and Δe.

The rules are framed as a 7 × 7 matrix, which is the conjunction of 2 input conditions e and Δe, to produce the output response at the intersection of row and column. In this case there are 49 possible logical product output responses. Table 2 illustrates the rule base used. To illustrate one typical rule,

Rule$_{ij}$: If e is $\mathcal{LN}$ and Δe is $\mathcal{ZE}$ then output is $\mathcal{MN}$.

The rules compute the weight and the functional overlap of the inputs and generate output responses. The output responses are combined across all 49 rules and defuzzified to a single value. Accordingly the rule matrix has been taken as

$$C = \begin{bmatrix} 0.857 & -0.857 & -0.571 & -0.571 & -0.571 & -0.285 & 0 \\ -0.857 & -0.571 & -0.571 & -0.571 & -0.285 & 0 & 0.285 \\ -0.571 & -0.571 & -0.571 & -0.285 & 0 & 0.285 & 0.571 \\ -0.571 & -0.571 & -0.285 & 0 & 0.285 & 0.571 & 0.571 \\ -0.571 & -0.857 & 0 & 0.285 & 0.571 & 0.571 & 0.571 \\ -0.285 & 0 & 0.285 & 0.571 & 0.571 & 0.571 & 0.857 \\ 0 & 0.285 & 0.571 & 0.571 & 0.571 & 0.285 & 0.285 \end{bmatrix}$$

Here every $C(i,j)$; $i = 1,\ldots,7$, $j = 1,\ldots,7$ corresponds to the c_i and c_j, the fuzzy consequent terms like LN (defined using Eqs. (7) and (8)) in Table 2.

The defuzzifier function is calculated as

$$q = \frac{\sum_{i=1}^{7}\sum_{j=1}^{7}\mu_i(e)\mu_j(\Delta e)C(i,j)}{\sum_{i=1}^{7}\sum_{j=1}^{7}\mu_i(e)\mu_j(\Delta e)} \tag{9}$$

For each value of e and Δe, produced for each measurement, the membership functions $\mu_i(e)$ and $\mu_j(\Delta e)$ are computed. The generated output using Eq. (9), is used to modify the variance of the observation error viz. R, in the equation for calculating the update of information state and information matrix (step 4 below). The fuzzy information filter, with the modified measurement covariance, is presented in Section 4.

Table 1
Definition of fuzzy variables.

Fuzzy term	c_i, c_j	σ_i^2, σ_j^2	Support
LN (Large Negative)	−0.857	2	[−1, −0.714]
MN (Medium Negative)	−0.572	2	[−0.714, −0.429]
SN (Small Negative)	−0.286	2	[−0.429, −0.143]
ZE (Zero)	0	2	[−0.143, 0.143]
SP (Small Positive)	0.286	2	[0.143, 0.429]
MP (Medium Positive)	0.572	2	[0.429, 0.714]
LP (Large Positive)	0.857	2	[0.714, 1]