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Design of Robust Fuzzy-Logic Tracker for Noise and Clutter Contaminated Trajectory based on Kalman Filter

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〈Abstract〉

Traditional methods for monitoring targets rely heavily on probabilistic data association (PDA) or Kalman filtering. However, achieving optimal performance in a densely congested tracking environment proves challenging due to factors such as the complexities of measurement, mathematical simplification, and combined target detection for the tracking association problem. This article analyzes a target tracking problem through the lens of fuzzy logic theory, identifies the fuzzy rules that a fuzzy tracker employs, and designs the tracker utilizing fuzzy rules and Kalman filtering.

Keywords : Clutter, Fuzzy Logic, Kalman Filter, Maneuvering, PDAF (Probabilistic Data Association Filter)

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1. Introduction

Recently, a substantial amount of research has been devoted to the standard Kalman filter-based target tracker and fuzzy logic based control algorithms [1-3]. Target tracking is the estimation of actual value in accordance with sensor-obtained target measurements. Due to the measurement noise of sensors and the unpredictability of whether the measurement is from the target or clutter, i.e. clutter, these measurements are inaccurate in the actual world. When random noise is the source of inaccuracy, the Kalman filter exhibits satisfactory tracking performance; however, it has one fatal flaw. It is due to the assumption that the probability of detection is one hundred percent. In a practical setting, the tracking performance of a solitary Kalman filter is likely to be suboptimal owing to the presence of debris. In order to compensate for these errors, a probabilistic data association filter is the proposed algorithm. This filter, which is comprised of multiple Kalman filters, determines the weights of measurements included in a region established around the estimated position produced by each Kalman filter (i.e., the data association gate). Each measurement is assigned a weight proportional to the likelihood that it originated from the target. An additional composite measurement is produced by summing the weighted values of every measurement taken within the gate.

Too many simplifying assumptions and being too restrictive to deal with the complexity of tracking problems in a real environment are the flaws of these conventional approaches. Not withstanding this, the most significant drawback of PDAF is its intrinsic bivalent nature. A phase within the PDAF target tracking procedure computes the target likelihood and compares it to the standard value. The target is proclaimed present if the value surpasses the threshold; otherwise, it is not declared. It is evident that a bivalent nature is present. An element of this kind is not exempt from the gate boundary. It is indisputable that such a method of classification cannot accurately represent reality. Nevertheless, by employing fuzzy logic and the level of membership function, this issue can be resolved. Consequently, this article contrasts the performance of a fuzzy logic tracker developed with Kalman filtering to that of the conventional PDAF.

2. Probabilistic Data Association Filter

The proposed algorithm, known as the probabilistic data association filter (PDAF), is designed to address the limitations of the traditional single Kalman filter. As in the real world, it is a suboptimal Bayesian filter for tracking a single target in a cluttered environment. Prior to anything else, this algorithm undergoes validation for every measurement provided by multiple Kalman filters. Once the data association gate is established with a measurement as its origin, the data is designated to be from the target if that measurement is included in that gate. In the absence of such evidence, the probability that the measurement originates from the target is deemed exceedingly low and is excluded from the final value calculation. Using this method, PDAF computes the weights of every validated measurement and produces the ultimate estimated value by summing the Bayesian components of these weights. The probability that each measurement originates from the target constitutes this weight. As a result, the error covariance matrix and the estimated value of the objective state derived from PDAF account for the uncertainty associated with the measurements.

2.1 Kalman Filter

The Kalman filter is a linear time-invariant dynamic system whose order is identical to that of the plant. Its input is the measured output $\boldsymbol{y}(t)$ of a probability dynamic system, and it determines the state estimation vector $\hat{\boldsymbol{x}}(t)$ in real-time by estimating the state vector $\boldsymbol{x}(t)$. To determine the most effective state estimation vector $\hat{\boldsymbol{x}}(t)$, the term "state estimation error $\tilde{\boldsymbol{x}}(t)$" is defined as follows [4].

$$\tilde{\boldsymbol{x}}(t) \equiv \boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t) \tag{1}$$

During steady-state, the average state estimation error $E\{\tilde{\boldsymbol{x}}(t)\}$ is zero, whereas the covariance matrix $\boldsymbol{P} = E[\tilde{\boldsymbol{x}}(t)\tilde{\boldsymbol{x}}(t)^T]$ does not equal to zero. Hence, to determine the optimal state estimation vector $\hat{\boldsymbol{x}}(t)$, it is necessary to minimize the error covariance matrix $\boldsymbol{P}$. At time k, the linear system is assumed to be defined by the following equations.

$$x_{k+1} = A_k x_k + B_k u_k + \nu_k \tag{2}$$

$$y_k = C_k x_k + \omega_k \tag{3}$$

The fundamental equations of the Kalman filter in this instance are as follows: A block diagram illustrates the Kalman filter's basic architecture in Fig. 1.

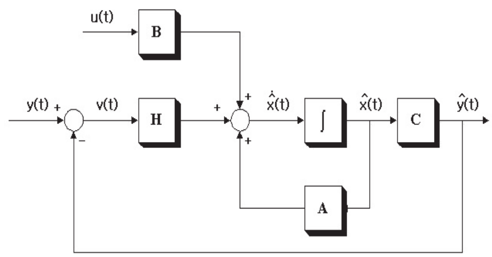

Fig. 1 The structure of Kalman Filter

$$\hat{x}_{k+1/k} = A_k \hat{x}_{k/k} + B_k u_k \tag{4}$$

$$\hat{x}_{k+1/k+1} = \hat{x}_{k+1/k} + H_{k+1}\left[y_{k+1} - C_{k+1}\hat{x}_{k+1/k}\right] \tag{5}$$

$$P_{k+1/k} = A_k P_{k/k} A_k^T + Q_k \tag{6}$$

$$P_{k+1/k+1} = P_{k+1/k} - H_{k+1} S_{k+1} H_{k+1}^T \tag{7}$$

$$H_{k+1} = P_{k+1/k} C_{k+1}^T S_{k+1}^{-1} \tag{8}$$

$$S_{k+1} = C_{k+1} P_{k+1/k} C_{k+1}^T + R_{k+1} \tag{9}$$

The definitions of each matrix and variable are given below [5].

x_k : target state vector
u_k : system input vector
y_k : measurement vector
A_k : state transition matrix
B_k : input matrix

C_k : measurement matrix
ν_k : plant noise vector
ω_k : measurement noise vector

Assumption underlying the Kalman filter: the measurement center is devoid of any ambiguity. Its probability of being emitted from the target is therefore one hundred percent at the time of detection. Nonetheless, non-target disturbances do occur in the actual surveillance environment. Moreover, the background noise completely obscures the target signals, rendering them undetectable. Real-world tracking performance cannot be deemed adequate by a single Kalman filter due to the aforementioned flaws.

2.2 Probabilistic Data Association Filter

The estimation of PDAF at real value consists of three distinct stages. The initial phase entails the validation of measurements. The establishment of data association in a cluttered environment commences with the substantiation of a sensor measurement through the process of measurement validation. The association probability between real target data and sensor measurements is computed by employing the probabilistic distance between the predicted target data for the subsequent scan and the measurements. An extremely remote hypothesis is made that the measurements indicating that this distance is enormous are, at most, coincident with genuine data. Thus, disregarding these does not significantly affect the overall performance, and the calculation burden of the tracking system can be reduced.

The subsequent stage involves the computation of the probability of each association using validated measurements. The sensor accepts measurements that contain both measurements from the target and noise introduced by the sensor environment; therefore, it is necessary to accurately determine the measurement using antecedent state information. Fig. 2 illustrates the PDAF block diagram.

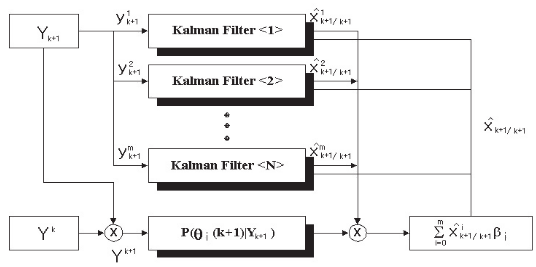

Fig. 2 Probabilistic Data Association Filter

There may be m measurements at any given time k in which the signal amplitude is greater than the threshold for detection. The collection of detected data Y_k is denoted as and the accumulation of measurements from the beginning of the monitoring period to time k is denoted as Y^k. Then the subsequent event is defined. Equation 10 stands for the event that ith measurement is correlated with the target and Equtaion 11 shows the event that no detection is from the target.

$$\theta_i(k)\ ,\ i=1,\cdots,m \tag{10}$$

$$\theta_0(k) \tag{11}$$

The probability of these events being conditional on the set of cumulative measurements is as follows:

$$\beta_i(k) \equiv P(\theta_i(k) \mid Y^k) \ , \ i=0,\cdots,m \qquad (12)$$

$$\sum_{i=0}^{m} \beta_i(k) = 1 \qquad (13)$$

Based on the fundamental assumption of PDAF, the Kalman filter is subsequently described as follows [6].

$$\hat{x}_{k+1/k} = A_k \hat{x}_{k/k} + B_k u_k \qquad (14)$$

$$\hat{x}^i_{k+1/k+1} = \hat{x}_{k+1/k} + H_{k+1}\left[y^i_{k+1} - C_{k+1}\hat{x}_{k+1/k}\right] \qquad (15)$$

Filter gain equation is,

$$H_{k+1} = P_{k+1/k} C^T_{k+1} S^{-1}_{k+1} \qquad (16)$$

$$S_{k+1} = C_{k+1} P_{k+1/k} C^T_{k+1} + R_{k+1} \qquad (17)$$

The covariance of error regarding the value estimated for the state is

$$P_{k+1/k+1} = P_{k+1/k} - W_{k+1} S_{k+1} W^T_{k+1} \qquad (18)$$

$$P_{k+1/k} = A_k P_{k/k} A^{T+}_k Q_k \qquad (19)$$

The posterior probability $\beta_i(k)$ that the measurement originates from the target can be determined by calculating each equation in a sequential fashion [7].

$$\beta_i(k) \equiv P(\theta_i(k) | Y^k) \ , \ i=0,\cdots,m_k \qquad (20)$$

$$\beta_i(k) = \frac{\exp\{-r_i(k)^T S(k)^{-1} r_i(k)/2\}}{b(k) + \sum_{i=1}^{m} \exp\{-r_i(k)^T S(k)^{-1} r_i(k)/2\}} \qquad (21)$$

$$\beta_0(k) = \frac{b(k)}{b(k) + \sum_{i=1}^{m} \exp\{-r_i(k)^T S(k)^{-1} r_i(k)/2\}} \qquad (22)$$

$$b(k) = (2\pi)^{M/2}(CV(k)/c_M \eta^M)(1-P_D)/P_D \qquad (23)$$

The ultimate stage involves producing the final estimation value, which is a weighted sum of measurements incorporating the probability of association.

$$\hat{x}_{k+1/k+1} = \sum_{i=1}^{m_{k+1}} \hat{x}^i_{k+1/k+1} \beta_i(k) \qquad (24)$$

3. Fuzzy-Logic Tracker Design

The objective of fuzzy-logic tracker design is to produce a tracker that exhibits enhanced efficacy in a real-world setting. Real-world clutter is caused by factors such as sensor noise, plant noise, non-target disturbance, and so forth. Additionally, noise is not typically uniformly distributed nor does it exhibit temporal constancy. This property suggests that for the tracker to function effectively in a given environment, it must be adaptable. When this occurs, fuzzy logic can demonstrate satisfactory performance. The target tracker that employs fuzzy logic is capable of excluding the bivalent nature of PDAF, establishing fuzzy rules through the application of expert knowledge, and practically implementing them due to the lax constraints on mathematical assumptions. The fuzzy logic tracker, akin to the PDA tracker, employs a

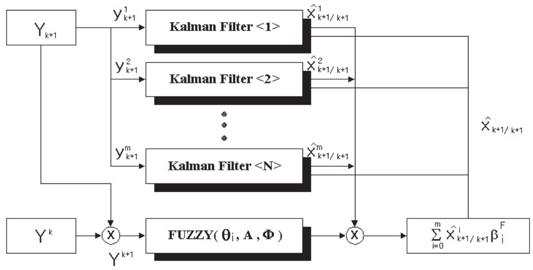

Fig. 3 Fuzzy-Logic Tracker

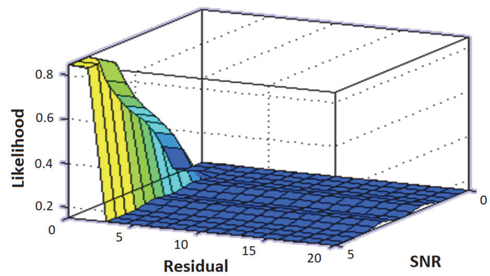

Fig. 4 Membership Function Surface

Kalman filter to dynamically modify the trajectory in response to acquired measurements. The only distinction is that fuzzy logic is used to generate the association likelihood between the measured and actual trajectory. Fig. 3 illustrates the configuration of a fuzzy-logic tracker.

The fuzzy-logic tracker described in this article is concerned with the Kalman filter residual and the signal strength. In order to determine fuzzy rules and membership functions, association likelihood is utilized as the output and these two values are used as input. Table 1 shows the fuzzy rules utilized in this study as follows:

Table 1. Fuzzy Rules

SNR / Residual	High	High moderate	Moderate	Low Moderate	Low
Far	moderate	moderate	low moderate	low	low
Middle far	moderate	moderate	low moderate	low	low
Middle	high moderate	moderate	low moderate	low	low
Middle close	high	high moderate	moderate	low moderate	low
Close	high	high moderate	moderate	low moderate	low

Fig. 4 depicts the surface of the membership function.

4. Numerical Validation

This article addresses the tracking problem of a moving target with a maneuvering period in one-dimensional space. Between 60 and 140 seconds, the target exhibits a point of maneuvering, while its motion is uniform in all other areas. The inclusion of uniform noise and debris in the simulation results in the generation of an environment that closely resembles the real world. And the matrix A, C, Q, and R used to state the equation, the covariance matrix of state estimation error, and the gain equation of the Kalman filter are presumed to be the following.

$$A = 1 \ , \ C = 1 \ , \ Q = (bet * \sigma)^2 \tag{25}$$

σ is the maximum value of autocorrelation function and bet is assumed to be 0.02 by experience.

$$bet = 0.02 \ , \ R = 0.007 \tag{26}$$

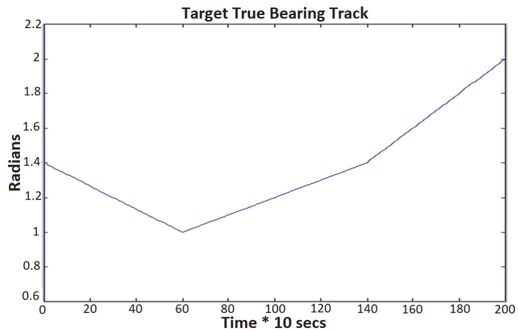

Fig. 5 True Bearing of the Target

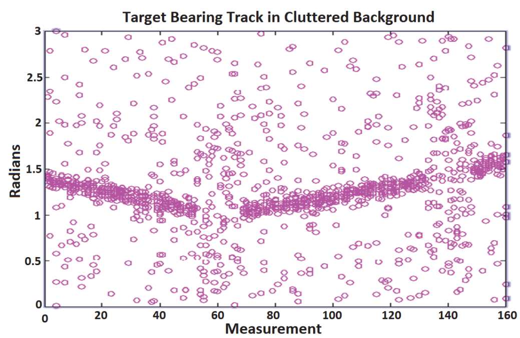

Fig. 6 Trajectory corrupted by noise and clutter

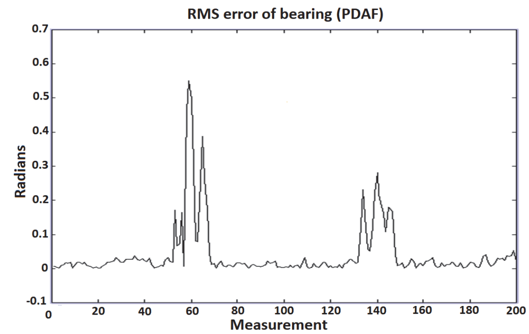

Fig. 7 RMS error of bearing (PDAF)

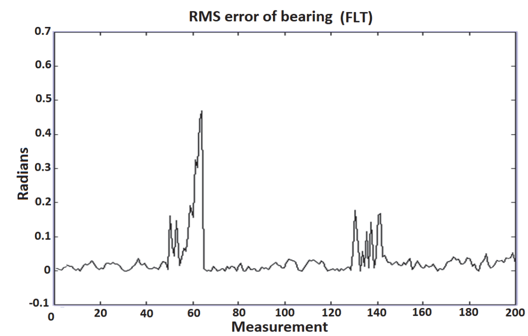

Fig. 8 RMS error of bearing (FLT)

Fig. 5 shows the true bearing of the target and Fig. 6 shows the trajectory corrupted by noise and clutter. Based on simulation outcomes, it can be observed that the RMS error of the fuzzy-logic tracker is comparatively lower than that of the PDA tracker during maneuvering, specifically around periods 60 and 140, as shown in Fig. 7 and 8. Thus, it is possible to conclude that the fuzzy-logic tracker performs more effectively in that situation. However, the RMS error of the fuzzy-logic tracker is marginally greater than that of the PDA tracker at non- maneuvering points.

5. Conclusion

In this study, we devised a fuzzy-logic tracker that demonstrates enhanced performance in a practical scenario, with the intention of rectifying the shortcomings of target trackers employing traditional PDAF and evaluating their performance and characteristics. As previously stated, fuzzy-logic trackers exhibit superior maneuverability.

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