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# Adaptive Target Tracking by Noise-Estimated Particle filter

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This paper proposes a new radar tracking filter named Noise-estimate Particle Filter (NPF). Kalman filter and particle filter are popular filtering techniques for target tracking. The tracking performance of the Kalman filter severely depends on the setting of several parameters such as system noise and observation noise. However, it is an open problem how to choose proper parameters for various scenarios, and they are often regulated in trial-and-error manner. The proposed filter estimates proper noise parameters of a Kalman filter on-line based on a scheme of particle filter. Simulation results show that the proposed filter has higher tracking performance in various scenarios than conventional Kalman filter and particle filter.

**Keywords:** Radar tracking, Particle filter, Kalman filter, Marginalized Particle Filter, Rao-Blackwellization

## 1. Introduction

Target tracking is a fundamental technique in not only computer vision but also various application fields. For example, in air traffic control by a radar sensor, multiple high-speed flight vehicles must be tracked simultaneously without lost-tracking while estimating their velocities and heights. However, in general, radar data is severely corrupted by noise due to atmospheric conditions or radar reflection property of the target, and it is still challenging to track targets stably under severe noisy condition.

For target tracking, a time series filter is very effective to suppress noise in sensory data and track targets smoothly and stably. In a time series filter, the current target position, which is estimated based on past observation and a motion model, are merged with current observation and the optimum position is derived. Especially, the time series filter which removes the noise component in the radar data and estimates the current position and velocity of the target is called "tracking filter".

Kalman filter is the most popular and widely-used tracking filter and has been applied to various applications so far. Based on the assumptions on linear and gaussian noise in sensory data, this filter estimates the statistically-optimized state of the target. Uniform linear motion is usually adopted as a motion model in simple Kalman filter. In case that target motion does not follow the uniform linear model, a system noise parameter which should be adjusted beforehand to absorb the system error affects the tracking performance severely. However, it is an open problem how to choose a proper value of the system noise parameter beforehand for various scenarios such as non-linear motion or rapid ac-

celeration/deceleration. In addition, an observation error which represents the accuracy of sensor/radar and has to be adjusted beforehand affects the performance of the Kalman filter, too. The observation model is also difficult to be set appropriately for various targets with a variety of shapes, motion directions, heights, distances, etc. Currently, a target tracking system based on Kalman filter has to be designed with proper system parameters in a try-and-error manner to meet the desired performance<sup>(1)</sup>.

In few decades, particle filter has been attracting much attention as a high-performance tracking filter. In particle filter, instead of estimating the probability distribution of the object state from the past observation and motion model in a parametric way, the probability distribution is represented by a set of particles. Each particle has a weight which represents the probability of the state of the particle. The particle is updated and re-sampled according to the Bayesian recursion equation.

Particle filter has been applied to various applications such as human tracking, state estimation, etc.<sup>(2)~(8)</sup>. Particle filter does not depend on the assumption of linear or gaussian noise, and is able to be applied for various systems even with non-linear and non-gaussian noise. However, the particle filter is less effective than the optimized Kalman filter for a target moving by a motion model, and the improvement of the tracking performance for various conditions is an open problem in particle filter.

This paper proposes a new tracking filter named the noise-estimated particle filter (NPF), which combines Kalman filter and particle filter. As mentioned above, Kalman filter is an optimum filter in case that the motion model of targets and observation model of sensor/radar are correctly provided. In the proposed filter, instead of estimating the state of the target such as position or velocity directly, the system error and the observation error are estimated on-line by particle-filter based approach. More correctly, the state of the tar-

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get is estimated based on Kalman filter, and its motion noise and observation noise are optimized by particle filter. Since the critical parameters of the Kalman filter are adjusted on-line according the observation, the proposed filter can be applied for a variety of target motions including not only uniform linear motion, but also sudden motion changes such as abrupt acceleration/deceleration or steep turn.

Some authors proposed combination filters of particle filter and Kalman filter<sup>(9)~(12)</sup>. Rao-Blackwellized Particle Filters<sup>(11)</sup> is the most popular technique in SLAM (Simultaneous Localization and Mapping). Localization and mapping procedures are separated in this filter and implemented using particle filter and Kalman filter, individually. Marginalized Particle Filter proposed Schon et al.<sup>(12)</sup> separates linear and nonlinear parts in the control system and assigns Kalman filter and particle filter separately. However, to our best knowledge, the proposed filter which utilizes particle filter for estimating the parameters of optimum Kalman filter has not been proposed so far. Satoh et al.<sup>(10)</sup> proposed a color-based tracking technique using Kalman Particle Filter<sup>(9)</sup>. As the noise-estimated particle filter proposed in the paper, the state of each particle is updated by Kalman filter. In their method, however, the observation noise is determined according to the weight of the particle and the state noise is determined previously.

## 2. Noise-estimated Particle Filter (NPF)

In the noise-estimated particle filter (NPF), a number of Kalman filters with a variety of sets of parameters runs simultaneously in a parallel way. As conventional particle filter, particles are re-sampled according to the errors between the estimated and observed states. By evaluating the performance of a number of Kalman filters with a variety of motion and observation parameters estimated adaptively, optimum target tracking which has similar high performance as optimized Kalman filter for a fixed condition is achieved for various motion patterns including uniform linear motion, abrupt acceleration/deceleration or steep turn.

### 2.1 Estimation of system and observation noise parameters

#### 2.1.1 Model definition

In the proposed tracking filter, each particle executes a similar process as Kalman filter individually. Firstly, a state space model for a target system is defined in each particle.

$$\mathbf{x}_{k+1}^i = \Phi_k \mathbf{x}_k^i + \mathbf{w}_k^i \dots \dots \dots (1)$$

$$\mathbf{z}_k^i = \mathbf{H} \mathbf{x}_k^i + \mathbf{v}_k^i \dots \dots \dots (2)$$

Eq.(1) is a motion model which represents a state transition and Eq.(2) is an observation model which shows the relation of estimated and observed states.  $\mathbf{x}_k^i$  is a state vector which contains position and velocity terms.  $\Phi_k$  is a state transition matrix and, in this paper, the uniform linear motion is assumed in all particles as follows.

$$\Phi_k = \begin{pmatrix} \mathbf{I} & \Delta t \mathbf{I} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} \dots \dots \dots (3)$$

where  $\Delta t$  is a sampling interval,  $\mathbf{I}$  is an identity matrix, and  $\mathbf{H} = (\mathbf{I} \ \mathbf{0})$  is an observation matrix.  $\mathbf{w}_k^i$  is a vector of system noise with an average  $\mathbf{0}$  and an error covariance matrix  $\mathbf{Q}_k^i$ , respectively.  $\mathbf{v}_k^i$  is also a vector of observation noise with an average  $\mathbf{0}$  and an error covariance matrix  $\mathbf{R}_k^i$ .

#### 2.1.2 Tracking process

A set of particles at time  $t_k$  is defined as  $\mathbf{X}_k = \{\mathbf{x}_k^i, w_k^i, q_k^i, r_k^i\}_{i=1}^N$ . Here,  $\mathbf{x}_k^i$  is a hypnosis for a state vector of position and velocity,  $w_k^i$  is a weight of each particle, and  $q_k^i$  and  $r_k^i$  are system and observation noises at each particle, respectively.

- (1) Produce  $N$  initial particles  $\mathbf{X}_0 = \{\mathbf{x}_0^i, w_0^i, q_0^i, r_0^i\}_{i=1}^N$ . The position, velocity, and system and observation noises are set with random numbers in particular ranges.

- (2) Execute step (a) to step (f) at time  $t_k$  ( $k = 1, \dots, T$ )

##### (a) Estimation

Execute prediction procedure in each particle by Kalman filter and estimate the current state from the previous state and the motion model.

$$\mathbf{x}_{k|k-1}^i = \Phi_k \mathbf{x}_{k-1|k-1}^i \dots \dots \dots (4)$$

$$\mathbf{P}_{k|k-1}^i = \Phi_k \mathbf{P}_{k-1|k-1}^i \Phi_k^T + \mathbf{Q}_k^i \dots \dots \dots (5)$$

where  $\mathbf{x}_{k|k-1}^i$  is an estimated state in each particle and  $\mathbf{x}_{k-1|k-1}^i$  is a previous state at time  $t_{k-1}$ .  $\mathbf{P}_{k|k-1}^i$  is an error covariance matrix in each particle and  $\mathbf{P}_{k-1|k-1}^i$  is a previous error covariance matrix at time  $t_{k-1}$ .

An error covariance matrix of system noise  $\mathbf{Q}_k^i$  at time  $t_k$  is obtained as follows.

$$\mathbf{Q}_k^i = \text{diag} \{q_k^{i2}, q_k^{i2}, q_k^{i2}\} \dots \dots \dots (6)$$

##### (b) Smoothing

To fit the estimated state with the current observation and estimate more accurate state, smoothing process in Kalman filter is applied in each particle.

$$\mathbf{x}_{k|k}^i = \mathbf{x}_{k|k-1}^i + \mathbf{K}_k^i [\mathbf{z}_k - \mathbf{H} \mathbf{x}_{k|k-1}^i] \dots \dots (7)$$

$$\mathbf{P}_{k|k}^i = (\mathbf{I} - \mathbf{K}_k^i \mathbf{H}) \mathbf{P}_{k|k-1}^i \dots \dots \dots (8)$$

$$\mathbf{K}_k^i = \mathbf{P}_{k|k-1}^i \mathbf{H}^T [\mathbf{H} \mathbf{P}_{k|k-1}^i \mathbf{H}^T + \mathbf{R}_k^i]^{-1} (9)$$

where  $\mathbf{x}_{k|k}^i$  is the estimated state of the particle at time  $t_k$ ,  $\mathbf{P}_{k|k}^i$  is the estimated error covariance matrix in each particle, and  $\mathbf{K}_k^i$  is a gain matrix.

The error covariance matrix of observation noise  $\mathbf{R}_k^i$  at time  $t_k$  is obtained as follows.

$$\mathbf{R}_k^i = \text{diag} \{r_k^{i2}, r_k^{i2}, r_k^{i2}\} \dots \dots \dots (10)$$

##### (c) Likelihood calculation

The likelihood  $p(\mathbf{z}_k | \mathbf{x}_{k|k}^i)$  at each particle is calculated as follows.

$$p(\mathbf{z}_k | \mathbf{x}_{k|k}^i) = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp \left( \frac{-d_i^2}{2\sigma_s^2} \right) \dots \dots (11)$$

where  $\sigma_s$  is a parameter to evaluate the accuracy of the hypnosis,  $d_i$  is an Euclidean distance between the position component in  $\mathbf{x}_{k|k}^i$  and the observed position  $\mathbf{z}_k$ . In the following experiments, we set  $\sigma_s = 300$ .

Next, the weight of each particle is updated according to the obtained likelihood as follows.

$$w_k^i = w_{k-1}^i p(\mathbf{z}_k | \mathbf{x}_{k-1}^i) \dots \dots \dots (12)$$

In addition, the sum of the weight of all particles is calculated by  $W_k = \sum_{i=1}^N w_k^i$  and the weight of each particle is normalized as  $w_k^i = w_k^i / W_k$ .

(d) State estimation

Estimated state  $\hat{\mathbf{x}}_k$  at time  $t_k$  is calculated by the weighted mean of  $N$  particles.

$$\hat{\mathbf{x}}_k \approx \sum_{i=1}^N w_k^i \mathbf{x}_{k|k}^i \dots \dots \dots (13)$$

(e) Resampling

Particles are re-sampled according to the probability proportional to the weight value  $w_k^i$ . As a result, particles with lower weight are removed and ones with higher weight are increased.

(f) Update

In contrast to updating position and/or velocity in a conventional particle filter, random offset values obtained with a normal distribution are added to the system noise  $q_k^i$  and the observation noise  $r_k^i$ , respectively.

$$q_k^i = q_k^i + \Delta q_k^i \dots \dots \dots (14)$$

$$r_k^i = r_k^i + \Delta r_k^i \dots \dots \dots (15)$$

where  $\Delta q_k^i$  and  $\Delta r_k^i$  are determined according to the normal random number with an average of 0 and a variances of  $\sigma_q$  and  $\sigma_r$ , respectively.  $\sigma_q$  and  $\sigma_r$  are predetermined parameters, and in the following experiments, we set  $\sigma_q = 0.1$  and  $\sigma_r = 5$ .

## 2.2 Estimation of system noise parameter

In the previous section, we showed a method to estimate the system and observation noise parameters simultaneously. However, in some cases, observation noise parameter is given according to the pre-defined accuracy of the sensor/radar, and on-line estimation is unnecessary.

Therefore, this section shows the another technique which estimates the system noise parameter only by the proposed noise-estimated particle filter.

### 2.2.1 Re-sampling procedure

As a result of preliminary experiments, it was shown that dynamic range of the optimum system noise is quite large for a radar tracking. For example, the optimum system noise for a turning motion is about few hundreds in the following experiments. On the other hand, the optimum value for straight motion should be almost zero to track accurately. To handle this large dynamic range, this section introduces a new re-sampling technique for radar tracking system.

This re-sampling technique utilizes two kinds of particles. By distributing them in different ranges, this filter can handle a large dynamic range of the system noise. The procedure of the re-sampling process is as follows.

(1) Beside a group of particles  $X_{k-1}$  at  $t_{k-1}$ , two

kinds of groups  $X_{k-1}^{\text{up}} = \left\{ \mathbf{x}_{k-1}^{\text{up},i}, w_{k-1}^{\text{up},i}, q_{k-1}^{\text{up},i} \right\}_{i=1}^N$ ,

$X_{k-1}^{\text{down}} = \left\{ \mathbf{x}_{k-1}^{\text{down},i}, w_{k-1}^{\text{down},i}, q_{k-1}^{\text{down},i} \right\}_{i=1}^N$  are produced.

We adopt two update processes of the system noises in each group as follows.

$$q_{k-1}^{\text{up},i} = q_{k-1}^{\text{up},i} + \Delta q_{k-1}^{\text{up},i} \dots \dots \dots (16)$$

$$q_{k-1}^{\text{down},i} = \alpha q_{k-1}^{\text{down},i} \dots \dots \dots (17)$$

In the above procedure,  $\Delta q_{k-1}^{\text{up},i}$  is given by a normal distribution of an average 0 and a variance  $\sigma_{\text{up}}$ , and  $\alpha$  is a uniform distribution within  $[0, \sigma_{\text{down}}]$ .  $\sigma_{\text{up}}$  and  $\sigma_{\text{down}}$  are control parameters. In the following experiments, we set  $\sigma_{\text{up}} \approx 100 \sim 1000$  and  $\sigma_{\text{down}} \approx 0.1$ . Consequently,  $X_k^{\text{up}}$  is a group of particles with a relatively large system noise and  $X_k^{\text{down}}$  is a group with a system noise smaller than the previous state.

(2) For these two groups of particles  $X_{k-1}^{\text{up}}$  and  $X_{k-1}^{\text{down}}$ , update, smoothing and likelihood calculation procedures are applied and new groups of particles at current period  $X_k^{\text{up}}$  and  $X_k^{\text{down}}$  are produced.

(3) Choose  $N$  particle according to the following rules.

- According to the observed data  $\mathbf{z}_k$ ,  $P$  particles of  $X_k^{\text{down}}$  are selected among the particles within the range of the sensor observation error. More correctly, particles which meet the following condition are selected.

$$|\mathbf{z}_k - \mathbf{x}_k^{\text{down},i}| < C \cdot \sigma_R \dots \dots \dots (18)$$

where  $\sigma_R$  is the accuracy of the radar.  $C$  is a gain parameter and controlled to be small if the variance of particles is large, and to be large if the variance is small, using a sigmoid function and the variance of all the particles  $\sigma_x$  as follows.

$$C = \frac{c}{1 + e^{-a(-\sigma_x + b)}} + d \dots \dots \dots (19)$$

where  $a \sim d$  are parameters of sigmoid function. In the following experiments, we set  $a = 40$ ,  $b = 0.14$ ,  $c = 1.9$ , and  $d = 0.1$ , and  $C$  is adjusted to vary from 0.1 to 3 according to the variance of particles.

- $N - P$  particles are selected among  $X_k^{\text{up}}$  according to the likelihood.

(4) Current particles  $X_k$  are replaced with  $N$  particles which are selected at Step (3).

## 3. Computer simulation

We conduct several computer simulations in order to compare the performance of the proposed noise-estimated particle filter, Kalman filter, and conventional particle filters optimized for straight and curved paths.

### 3.1 Simulation condition

We assume a radar sensor is placed at the origin of the coordinate and set the sampling interval as 0.5 [s], the accuracy of the radar as 30 [m] in distance and 0.2 [deg.] in azimuth and elevation angles. The target starts to move from 70 [km] apart from the radar toward the radar with a height of 10[km] and the velocity of 306 [m/s]. Two types of trajectories including straight and curved paths are tested.

For a scenario of the straight path, the target moves by the uniform linear motion between 0 to 150 [sec.]. For a scenario of the curved path, the target moves by the uniform linear motion between 0 to 50 [sec.] and

100 to 150 [sec.], and with the turning motion from 50 to 100 [sec.] during level flight. In this scenario, the target turns 1 or 4 times on horizontal plane.

We runs Monte-Carlo simulation in 50 times and evaluates the RMS (Root Mean Square) error. Four types of tracking filters are compared

- (1) Kalman filters which are adjusted to provide the best performance at straight path
- (2) Kalman filters which are adjusted to provide the best performance at curved path
- (3) Conventional particle filter
- (4) Proposed noise-estimated particle filter

The number of particles are 200 for conventional particle filter and 100 for noise-estimated particle filter, which are determined experimentally.

**3.2 Estimation of system and observation noises** Tracking results for the proposed noise-estimated particle filter which estimates system and observation noises are shown in Fig.1. In Fig.1, KF\_Straight is the Kalman filter for straight trajectory, KF\_Curve is the Kalman filter for curved trajectory, PF is the conventional particle filter, and NPF\_QR is the proposed noise-estimated particle filter. In addition, the estimated system and observation noises for 4-turns trajectory are shown in Fig.2.

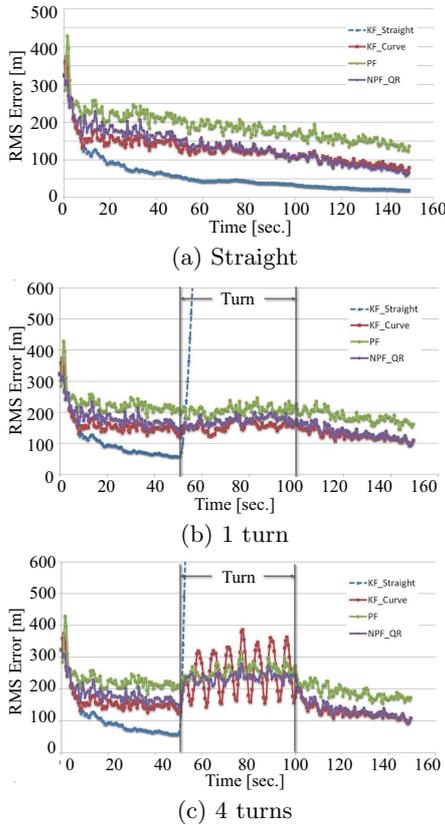


Fig. 1. Tracking error (system and observation noises are estimated)

The smoothing performance of the proposed noise-estimated particle filter (NPF\_QR) outperforms the conventional particle filter (PF), and is similar to the Kalman filter optimized for curved trajectory

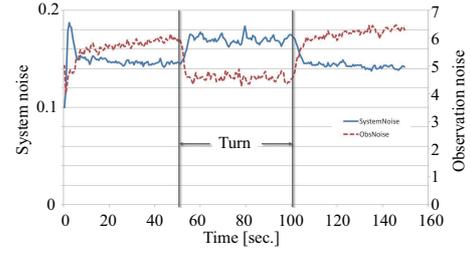


Fig. 2. Estimated system and observation noises (4 turns)

(KF\_Curve). Though the Kalman filter optimized for straight trajectory (KF\_Straight) shows the best performance in straight path, it cannot track the target while turning at all. In addition, though the tracking delay is occurred for the Kalman filter for curved trajectory (KF\_Curve) at 4-turns scenario, the accuracy of the proposed filter is similar to the conventional particle filter (PF). Consequently, it is confirmed that the proposed filter can be applied to various scenarios more adaptively than other conventional filters.

**3.3 Estimation of system noise** Tracking error for the proposed filter which estimates the system noise are shown in Fig.3. NPF\_Q indicates the proposed noise-estimated particle filter.

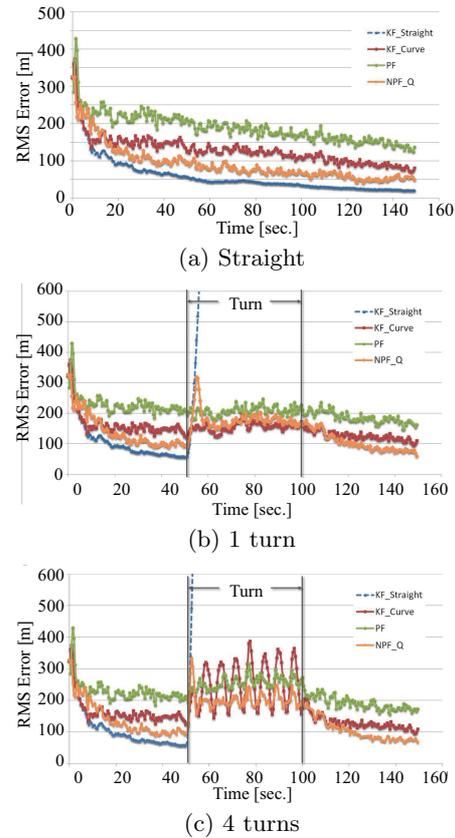


Fig. 3. Tracking error (system noise is estimated)

As shown in Fig.3, the tracking error for the straight trajectory is considerably suppressed against the conventional particle filter. Moreover, for the curved trajectory in 4-turns scenario, the tracking performance of

the proposed filter outperforms the conventional particle filter.

However, the large delay occurred just after starting turning motion temporarily and the transient response is observed. This is because, after tracking in a straight line for a while,  $X^{\text{down}}$  particles are increased and the system noise tends to be ignored, and thus the response for the curved trajectory is delayed.

#### 4. Conclusion

This paper proposed the new noise-estimated particle filter for a target tracking system. The proposed filter estimates the system and the observation noises in Kalman filter by using the particle filter and adapts the abrupt changes of the target motion characteristics.

We examined the tracking performance of the proposed noise-estimated particle filter by computer simulations for the radar tracking system, and confirmed that the proposed filter has high smoothing performance for the tracking error and high stability performance for sudden changes of the target motions.

This paper focused on the radar-based target tracking, however, the applications of the proposed noise-estimated particle filter is not limited to radar tracking and we can apply the proposed filter for a variety of vision-based tracking systems. We are going to apply the proposed filter for, for example, pedestrian tracking using distributed cameras and laser range finders in near future.

#### Acknowledgment

The present study was supported in part by a Grant-in-Aid for Scientific Research (B) (23360115).

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