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Performance analysis of two EM-based measurement bias estimation processes for tracking systems

Key words: Non-linear state-space model; Measurement bias; Extended Kalman filter; Extended Kalman smoothing; Expectation-maximization (EM) algorithm

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Motivations

1. In target tracking, the measurements collected by sensors can be biased in some real scenarios.

2. The measurement biases inherent in the sensors will enter into the fusion process and lead to false tracks.

3. To accurately estimate target trajectory, the effect of those biases must be eliminated by means of estimation and correction.

Main ideas

1. In contrast to the existing algorithms in which the measurement bias is assumed to be constant, the proposed algorithm assumes that the bias is a random variable.

2. Two state-space models are used to differently formulate the impact of the bias on target tracking.

3.Two estimation processes are proposed to estimate the measurement bias.

4. The estimation performance is theoretically analyzed.

Method

1. The extended Kalman filter is used to linearize the non-linear state-space models.

2. The expectation-maximization (EM) algorithm is used to derive two distinct bias estimation processes, with the assistance of extended Kalman filter and smoother.

3. The performance is analyzed using the underlying principle of the EM algorithm and the inherent structure of two state-space models.

Major results

1. Estimation results of bias variance

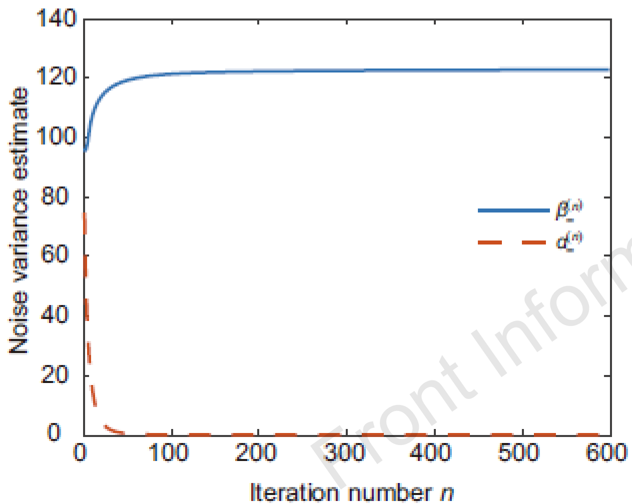

Fig. 2 Estimates $\alpha_-^{(n)}$ and $\beta_-^{(n)}$ of model 1 w.r.t. the iteration number n

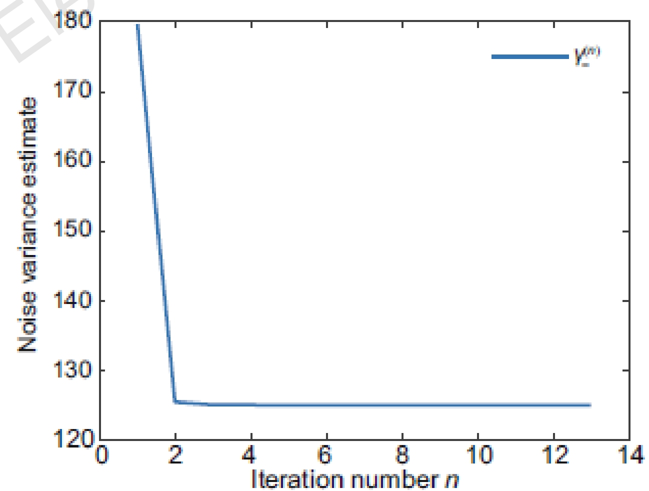

Fig. 3 Estimate $\gamma_-^{(n)}$ of model 2 w.r.t. the iteration number n

Major results (Cont’d)

Estimation results of bias variance

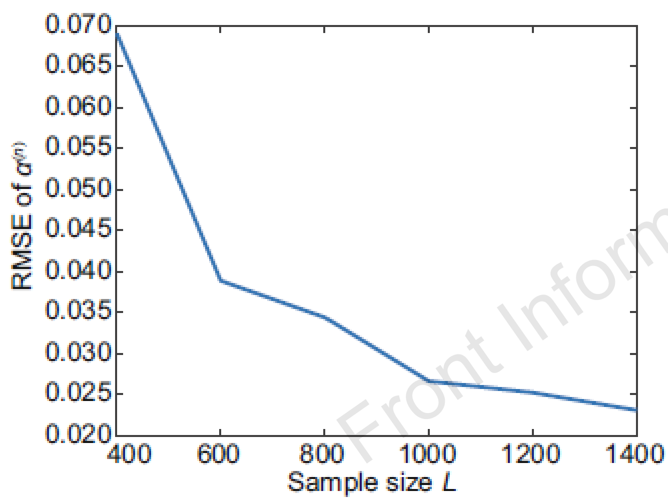

Fig. 5 Root mean square error (RMSE) of $\alpha^{(n)}$ w.r.t. the sample size L

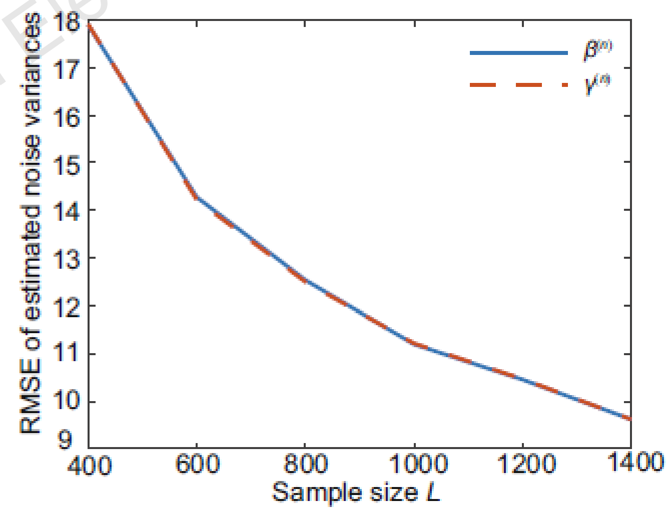

Fig. 6 Root mean square error (RMSE) of $\beta^{(n)}$ and $\gamma^{(n)}$ w.r.t. the sample size L

Major results (Cont'd)

2. Estimation results of bias mean and target positions

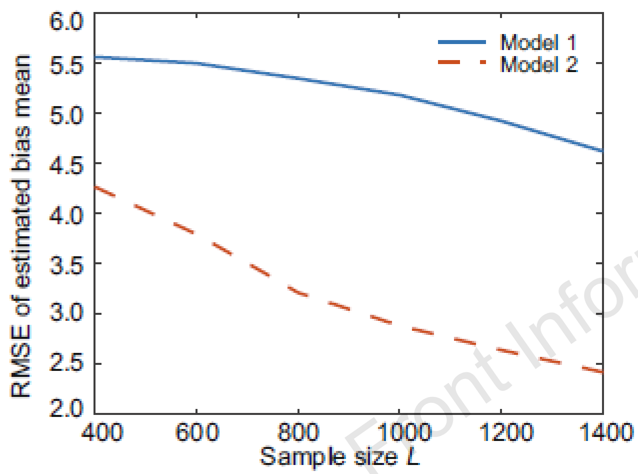

Fig. 7 Root mean square error (RMSE) of $\mu_b^{(n)}$ w.r.t. the sample size L

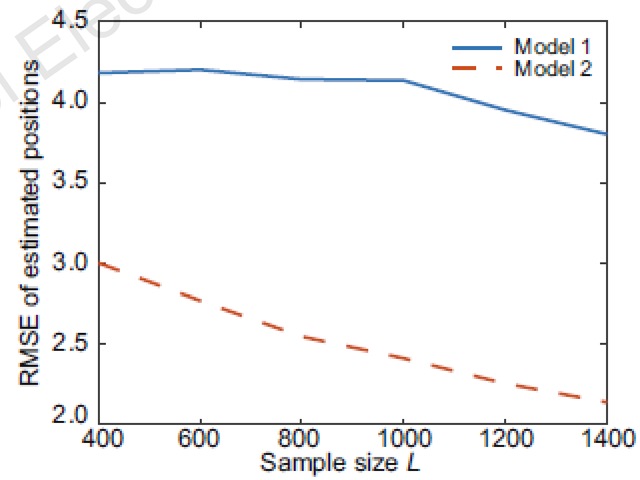

Fig. 8 Root mean square error (RMSE) of estimated target positions w.r.t. the sample size L

Conclusions

1. After the measurement bias is differently formulated in two state-space models, two EM-based estimation processes are correspondingly proposed.

2. The performance of two estimation processes is theoretically analyzed, following which their link and difference are revealed.

3. Theoretical analysis and simulations validate that the second one performs better that the first one, also with a simpler structure and faster convergence speed.