

Supplementary Material for the paper “A Bayesian Robust Kalman Smoothing Framework for State-Space Models with Uncertain Noise Statistics”

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In this supplement, we provide more details on the likelihood function $f(\mathcal{Y}_L|\boldsymbol{\theta})$ needed for obtaining the posterior effective noise statistics based on the Metropolis Hastings technique.

Algorithm 1 summarizes the procedure for computing the likelihood function of the parameter $\boldsymbol{\theta} = [\theta_1, \theta_2]$ given a sequence of observations $\mathcal{Y}_L = \{\mathbf{y}_0, \dots, \mathbf{y}_L\}$ up to time L . The inputs to this algorithm are the sequence of observations \mathcal{Y}_L , the initial conditions $\mathbb{E}[\mathbf{x}_0]$ and $\text{cov}[\mathbf{x}_0]$, and matrices $\boldsymbol{\Phi}_k$, $\boldsymbol{\Gamma}_k$, \mathbf{H}_k , \mathbf{Q}^{θ_1} , and \mathbf{R}^{θ_2} characterizing the parameterized state-space model in (1) and (2).

In order to compute the likelihood function in Line 17, which is based on equation (39) in the paper, we first need to obtain S_L and matrices $\boldsymbol{\Sigma}_L$ and \mathbf{M}_L using recursive calculations outlined in lines 8 to 14. After the recursive calculations, $\boldsymbol{\Delta}_L$ and \mathbf{G}_L can be computed using $\boldsymbol{\Sigma}_L$ and \mathbf{M}_L .

In each iteration of the recursive calculations, first $\boldsymbol{\Sigma}_{k+1}$ is obtained using $\boldsymbol{\Lambda}_k$. Then $\boldsymbol{\Sigma}_{k+1}$ along with $\boldsymbol{\Lambda}_k$, $\boldsymbol{\Sigma}_k$, and \mathbf{M}_k is used to calculate \mathbf{M}_{k+1} . In the next step, $\boldsymbol{\Sigma}_{k+1}$ and \mathbf{M}_{k+1} can be used to update the value of S_k to S_{k+1} . Also, $\boldsymbol{\Lambda}_{k+1}$ is found using $\boldsymbol{\Sigma}_{k+1}$. Finally, \mathbf{W}_{k+1} can be obtained via $\boldsymbol{\Sigma}_{k+1}$ and \mathbf{M}_{k+1} .

Algorithm 1 Likelihood Function Computation

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1: input:  $\mathcal{Y}_L = \{\mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_L\}$ ,  $E[\mathbf{x}_0]$ ,  $\text{cov}[\mathbf{x}_0]$ ,  $\Phi_k$ ,  $\Gamma_k$ ,  $\mathbf{H}_k$ ,  $\mathbf{Q}^{\theta_1}$ ,  $\mathbf{R}^{\theta_2}$ 
2: output:  $f(\mathcal{Y}_L|\theta)$ 
3:  $S_0 \leftarrow 1$  ▷ the initialization step for  $S_k$ 
4:  $\Sigma_0 \leftarrow \text{cov}[\mathbf{x}_0]$  ▷ the initialization step for  $\Sigma_k$ 
5:  $\mathbf{M}_0 \leftarrow E[\mathbf{x}_0]$  ▷ the initialization step for  $\mathbf{M}_k$ 
6:  $\tilde{\mathbf{Q}}_0^{\theta_1} \leftarrow \Gamma_0 \mathbf{Q}^{\theta_1} \Gamma_0^T$ 
7:  $\Lambda_0^{-1} \leftarrow \Phi_0^T (\tilde{\mathbf{Q}}_0^{\theta_1})^{-1} \Phi_0 + \mathbf{H}_0 (\mathbf{R}^{\theta_2})^{-1} \mathbf{H}_0 + \Sigma_0^{-1}$  ▷ the initialization step for  $\Lambda_k$ 
8: for  $k = 0 : L - 1$  do
9:    $\tilde{\mathbf{Q}}_k^{\theta_1} \leftarrow \Gamma_k \mathbf{Q}^{\theta_1} \Gamma_k^T$ 
10:   $\Sigma_{k+1}^{-1} \leftarrow (\tilde{\mathbf{Q}}_k^{\theta_1})^{-1} - (\tilde{\mathbf{Q}}_k^{\theta_1})^{-1} \Phi_k \Lambda_k \Phi_k^T (\tilde{\mathbf{Q}}_k^{\theta_1})^{-1}$  ▷ equation (42)
11:   $\mathbf{M}_{k+1} \leftarrow \Sigma_{k+1} (\tilde{\mathbf{Q}}_k^{\theta_1})^{-1} \Phi_k \Lambda_k (\mathbf{H}_k^T (\mathbf{R}^{\theta_2})^{-1} \mathbf{y}_k + \Sigma_k^{-1} \mathbf{M}_k)$  ▷ equation (43)
12:   $S_{k+1} \leftarrow S_k \sqrt{\frac{|\Lambda_k| |\Sigma_{k+1}|}{|\tilde{\mathbf{Q}}_k^{\theta_1}| |\Sigma_k|}} \mathcal{N}(\mathbf{y}_k; \mathbf{0}_{m \times 1}, \mathbf{R}^{\theta_2}) \exp \left( \frac{\mathbf{M}_{k+1}^T \Sigma_{k+1}^{-1} \mathbf{M}_{k+1} + \mathbf{W}_k^T \Lambda_k \mathbf{W}_k - \mathbf{M}_k^T \Sigma_k^{-1} \mathbf{M}_k}{2} \right)$ 
    ▷ equation (44)
13:   $\Lambda_{k+1}^{-1} \leftarrow \Phi_{k+1}^T (\tilde{\mathbf{Q}}_{k+1}^{\theta_1})^{-1} \Phi_{k+1} + \mathbf{H}_{k+1} (\mathbf{R}^{\theta_2})^{-1} \mathbf{H}_{k+1} + \Sigma_{k+1}^{-1}$  ▷ equation (45)
14:   $\mathbf{W}_{k+1} \leftarrow \mathbf{H}_{k+1}^T (\mathbf{R}^{\theta_2})^{-1} \mathbf{y}_{k+1} + \Sigma_{k+1}^{-1} \mathbf{M}_{k+1}$  ▷ equation (46)
15:   $\Delta_L^{-1} \leftarrow \mathbf{H}_L^T (\mathbf{R}^{\theta_2})^{-1} \mathbf{H}_L + \Sigma_L^{-1}$  ▷ equation (40)
16:   $\mathbf{G}_L \leftarrow \Delta_L (\mathbf{H}_L^T (\mathbf{R}^{\theta_2})^{-1} \mathbf{y}_L + \Sigma_L^{-1} \mathbf{M}_L)$  ▷ equation (41)
17:   $f(\mathcal{Y}_L|\theta) \leftarrow S_L \sqrt{\frac{|\Delta_L|}{|\Sigma_L|}} \mathcal{N}(\mathbf{y}_L; \mathbf{0}_{m \times 1}, \mathbf{R}^{\theta_2}) \exp \left( \frac{1}{2} (\mathbf{G}_L^T \Delta_L^{-1} \mathbf{G}_L - \mathbf{M}_L^T \Sigma_L^{-1} \mathbf{M}_L) \right)$  ▷
    equation (39)
18: return  $f(\mathcal{Y}_L|\theta)$ 

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