Score Evaluation within the Extended Square-root Information Filter

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Introduction

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[P. Park&T. Kailath, 1995] The extended Square Root Information Filter (eSRIF):

- √ avoids numerical instabilities arising from computational errors;
- √ appears to be better suited to parallel implementation and to very large scale integration (VLSI) implementation.

Problem Statement

Consider the discrete-time linear dynamic stochastic system

$$x_{t+1} = F_t x_t + G_t w_t, \qquad t = 0, 1, \ldots, N, \tag{1}$$

$$z_t = H_t x_t + v_t, \qquad t = 1, 2, \ldots, N, \tag{2}$$

with the system state $x_t \in \mathbb{R}^n$, the state disturbance $w_t \in \mathbb{R}^q$, the observed vector $z_t \in \mathbb{R}^m$, and the measurement error $v_t \in \mathbb{R}^m$,

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$$\mathbf{E}\left\{ \begin{bmatrix} x_0 & w_t & v_t \end{bmatrix} \right\} = \begin{bmatrix} \bar{x}_0 & 0 & 0 \end{bmatrix} \quad \text{and}$$

Problem Statement

$$\mathbf{E}\left\{\begin{bmatrix}(x_0-\bar{x}_0)\\ w_t\\ v_t\end{bmatrix}\begin{bmatrix}(x_0-\bar{x}_0)\\ w_t\\ v_t\end{bmatrix}^T\right\}=\begin{bmatrix}P_0 & 0 & 0\\ 0 & Q_t & 0\\ 0 & 0 & R_t\end{bmatrix}$$

and $\mathbf{E}\left\{w_t w_{t'}^T\right\}=0$, $\mathbf{E}\left\{v_t v_{t'}^T\right\}=0$ if $t\neq t'$.

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and $\mathbf{E}\left\{w_t w_{t'}^T\right\}=0$, $\mathbf{E}\left\{v_t v_{t'}^T\right\}=0$ if $t\neq t'$. Assume the system is parameterized by a vector $\theta\in\mathbb{R}^p$ of unknown system parameters. This means that all the above characteristics, namely F_t, G_t, H_t, $P_0\geq 0$, $Q_t\geq 0$ and $R_t>0$ can depend upon θ (the corresponding notations $F_t(\theta)$, $G_t(\theta)$ and so on, are suppressed for the sake of simplicity).

Problem Statement

For example, (1), (2) may describe a discrete autoregressive (AR) process observed in the presence of additive noise

$$x_{t+1} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ \theta_1 & \theta_2 & \theta_3 & \dots & \theta_p \end{bmatrix} x_t + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \gamma \end{bmatrix} w_t,$$

$$z_t = \begin{bmatrix} 0 & 0 & \dots & 1 \end{bmatrix} x_t + v_t.$$

In this case θ are the unknown AR parameters which need to be estimated.

Problem Statement

The negative Log Likelihood Function (LLF) for system (1), (2) is given by

$$L_\theta\left(Z_1^N\right) = \frac{1}{2}\sum_{t=1}^{N}\left\{\frac{m}{2}\ln(2\pi) + \ln(\det(R_{e,t})) + e_t^T R_{e,t}^{-1} e_t\right\}$$

with $e_t \stackrel{\text{def}}{=} z_t - H_t\hat{x}_t$ being the zero-mean innovations whose covariance is determined as $R_{e,t} \stackrel{\text{def}}{=} E\{e_t e_t^T\} = H_t P_t H_t^T + R_t$ through matrix P_t, the error covariance of the time updated estimate $\hat{x}_t$ generated by the Kalman Filter.

Problem Statement

Let $l_\theta(z_t)$ denote the negative LLF for the t-th measurement z_t in system (1), (2), given measurements $Z_1^{t-1} \stackrel{\text{def}}{=} \{z_1, \ldots, z_{t-1}\}$, then

$$l_\theta(z_t) = \frac{1}{2}\left\{\frac{m}{2}\ln(2\pi) + \ln(\det(R_{e,t})) + e_t^T R_{e,t}^{-1} e_t\right\}. \qquad (3)$$

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By differentiating (3) we obtain

$$\frac{\partial l_\theta(z_t)}{\partial \theta_i} = \frac{1}{2}\frac{\partial}{\partial \theta_i}\left[\ln(\det(R_{e,t}))\right] + \frac{1}{2}\frac{\partial}{\partial \theta_i}\left[e_t^T R_{e,t}^{-1} e_t\right], \ i = \overline{1,p}. \qquad (4)$$

As can be seen the computation of (3) and (4) leads to implementation of a Kalman Filter (and its derivative with respect to each parameter) which is known to be unstable.

The eSRIF

[P. Park&T. Kailath, 1995]: assume that $\Pi_0 > 0$, $R_t > 0$ and F_t are invertible. Given $P_0^{-T/2} = \Pi_0^{-T/2}$ and $P_0^{-T/2}\hat{x}_0 = \Pi_0^{-T/2}\bar{x}_0$, then

$$O_t \left[\begin{array}{ccc|c} R_t^{-T/2} & -R_t^{-T/2}H_tF_t^{-1} & R_t^{-T/2}H_tF_t^{-1}G_tQ_t^{T/2} & -R_t^{-T/2}z_t \\ 0 & P_t^{-T/2}F_t^{-1} & -P_t^{-T/2}F_t^{-1}G_tQ_t^{T/2} & P_t^{-T/2}\hat{x}_t \\ 0 & 0 & I_q & 0 \end{array}\right]$$

$$= \left[\begin{array}{ccc|c} R_{e,t}^{-T/2} & 0 & 0 & -\bar{e}_t \\ -P_{t+1}^{-T/2}K_{p,t} & P_{t+1}^{-T/2} & 0 & P_{t+1}^{-T/2}\hat{x}_{t+1} \\ * & * & * & * \end{array}\right]$$

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where O_t is any orthogonal transformation such that the matrix on the right-hand side of the formula is block lower triangular.

The eSRIF

The eSRIF is a modification of the conventional one:

$$O_t \begin{bmatrix} R_t^{-T/2} & -R_t^{-T/2} H_t F_t^{-1} & R_t^{-T/2} H_t F_t^{-1} G_t Q_t^{T/2} \\ 0 & P_t^{-T/2} F_t^{-1} & -P_t^{-T/2} F_t^{-1} G_t Q_t^{T/2} \\ 0 & 0 & I_q \end{bmatrix} = \begin{bmatrix} R_{e,t}^{-T/2} & 0 & 0 \\ -P_{t+1}^{-T/2} K_{p,t} & P_{t+1}^{-T/2} & 0 \\ * & * & * \end{bmatrix}$$

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where O_t is any orthogonal transformation such that the matrix on the right-hand side of the formula is lower triangular.

The eSRIF

Remark. The predicted estimate now can be found from the entries of the post-array by solving the triangular system

$$\left(\tilde{P}_{t+1}^{-1/2}\right)\left(\hat{x}_{t+1}^{-}\right) = \left(\tilde{P}_{t+1}^{-1/2}\hat{x}_{t+1}^{-}\right). \tag{5}$$

The LLG in terms of the eSRIF

The Log Likelihood Gradient (LLG) in terms of the eSRIF is given by

$$\frac{\partial l_\theta(z_t)}{\partial \theta_i} = \frac{\partial}{\partial \theta_i}\left[\ln(\det(R_{e,t}^{1/2}))\right] + \bar{e}_t{}^T \frac{\partial \bar{e}_t}{\partial \theta_i}, \qquad i = 1, \ldots p,$$

where $R_{e,t}^{1/2}$ is a square-root factor of the matrix $R_{e,t}$, i. e. $R_{e,t} = R_{e,t}^{T/2} R_{e,t}^{1/2}$, and $\bar{e}_t$ are the normalized innovations, i. e. $\bar{e}_t = R_{e,t}^{-T/2} e_t$.

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$$\frac{\partial}{\partial \theta_i}\left[\ln\left(\det(R_{e,t}^{1/2})\right)\right] = \mathbf{tr}\left[R_{e,t}^{-1/2}\,\frac{\partial\left(R_{e,t}^{1/2}\right)}{\partial \theta_i}\right], \quad i = 1,\ldots,p,$$

where $\mathbf{tr}\left[\,\cdot\,\right]$ is a trace of matrix.

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where $\mathbf{tr}\left[\,\cdot\,\right]$ is a trace of matrix.

Finally, we obtain the expression for the LLG in terms of the eSRIF:

$$\frac{\partial l_\theta(z_t)}{\partial\theta_i} = -\,\mathbf{tr}\left[R_{e,t}^{1/2}\,\frac{\partial\left(R_{e,t}^{-1/2}\right)}{\partial\theta_i}\right] + \bar{e}_t^T\frac{\partial\bar{e}_t}{\partial\theta_i}, \; i = 1,\ldots,p. \quad (6)$$

LLG Evaluation

$$\frac{\partial l(z_t)}{\partial \theta_i} = -tr\left[\ R_{e,t}^{1/2}\ \frac{\partial\left(R_{e,t}^{-1/2}\right)}{\partial \theta_i}\right] + \ \bar{e}_t^T\ \frac{\partial \bar{e}_t}{\partial \theta_i},\ i = 1, \ldots, p. \qquad (6)$$

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$$O_t \left[\begin{array}{ccc|c} R_t^{-T/2} & -R_t^{-T/2} H_t F_t^{-1} & R_t^{-T/2} H_t F_t^{-1} G_t Q_t^{T/2} & -R_t^{-T/2} z_t \\ 0 & P_t^{-T/2} F_t^{-1} & -P_t^{-T/2} F_t^{-1} G_t Q_t^{T/2} & P_t^{-T/2} \hat{x}_t \\ 0 & 0 & I_q & 0 \end{array} \right]$$

$$= \left[\begin{array}{ccc|c} R_{e,t}^{-T/2} & 0 & 0 & -\bar{e}_t \\ -P_{t+1}^{-T/2} K_{p,t} & P_{t+1}^{-T/2} & 0 & P_{t+1}^{-T/2} \hat{x}_{t+1} \\ * & * & * & * \end{array} \right]$$

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LLG Evaluation

Lemma 1. Let

$$QA = L \quad (7)$$

where Q is any orthogonal transformation such that the matrix on the right-hand side of formula (7) is lower triangular and A is a nonsingular matrix. If the elements of A are differentiable functions of a parameter θ then the upper triangular matrix U in

$$Q'_\theta Q^T = \bar{U}^T - \bar{U} \quad (8)$$

is, in fact, the strictly upper triangular part of the matrix $QA'_\theta L^{-1}$:

$$QA'_\theta L^{-1} = \bar{L} + D + \bar{U} \quad (9)$$

where $\bar{L}$, D and $\bar{U}$ are, respectively, strictly lower triangular, diagonal and strictly upper triangular.

Algorithm LLG-eSRIF

I. For each θ_i, $i = 1, \ldots, p$, apply the eSRIF

$$O_t \left[\begin{array}{ccc|c} R_t^{-T/2} & -R_t^{-T/2} H_t F_t^{-1} & R_t^{-T/2} H_t F_t^{-1} G_t Q_t^{T/2} & -R_t^{-T/2} z_t \\ 0 & P_t^{-T/2} F_t^{-1} & -P_t^{-T/2} F_t^{-1} G_t Q_t^{T/2} & P_t^{-T/2} \hat{x}_t \\ 0 & 0 & I_q & 0 \end{array} \right]$$

$$= \left[\begin{array}{ccc|c} R_{e,t}^{-T/2} & 0 & 0 & -\bar{e}_t \\ -P_{t+1}^{-T/2} K_{p,t} & P_{t+1}^{-T/2} & 0 & P_{t+1}^{-T/2} \hat{x}_{t+1} \\ * & * & * & * \end{array} \right]$$

where O_t is any orthogonal transformation such that the matrix on the right-hand side of the formula is block lower triangular.

Algorithm LLG-eSRIF

II. For each θ_i, $i = 1, \ldots, p$, calculate

$$O_t \left[\begin{array}{ccc|c} \frac{\partial}{\partial \theta_i}\left(R_t^{-T/2}\right) & \frac{\partial}{\partial \theta_i}\left(S_t^{(1)}\right) & \frac{\partial}{\partial \theta_i}\left(S_t^{(2)}\right) & \frac{\partial}{\partial \theta_i}\left(S_t^{(3)}\right) \\ 0 & \frac{\partial}{\partial \theta_i}\left(S_t^{(4)}\right) & \frac{\partial}{\partial \theta_i}\left(S_t^{(5)}\right) & \frac{\partial}{\partial \theta_i}\left(S_t^{(6)}\right) \\ 0 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} X_i & Y_i & M_i & L_i \\ N_i & V_i & W_i & K_i \\ * & * & * & * \end{array} \right],$$

O_t is the same orthogonal transformation as in the eSRIF

and

$$S_t^{(1)} = -R_t^{-T/2} H_t F_t^{-1}, \quad S_t^{(2)} = R_t^{-T/2} H_t F_t^{-1} G_t Q_t^{T/2}, \quad S_t^{(3)} = -R_t^{-T/2} z_t,$$

$$S_t^{(4)} = P_t^{-T/2} F_t^{-1}, \quad S_t^{(5)} = -P_t^{-T/2} F_t^{-1} G_t Q_t^{T/2}, \quad S_t^{(6)} = P_t^{-T/2} \hat{x}_t.$$

Algorithm LLG-eSRIF

III. For each θ_i, $i = 1, \ldots, p$, compute

$$J_i = \begin{bmatrix} X_i & Y_i & M_i \\ N_i & V_i & W_i \end{bmatrix} \begin{bmatrix} R_{e,t}^{-T/2} & 0 & 0 \\ -P_{t+1}^{-T/2} K_{p,t} & P_{t+1}^{-T/2} & 0 \\ * & * & * \end{bmatrix}^{-1}.$$

Algorithm LLG-eSRIF

IV. For each θ_i, $i = 1, \ldots, p$, split the matrices

$$J_i = \overbrace{\left[\underbrace{L_i + D_i + U_i}_{m+n} \Big| \quad * * * \quad \right]}^{m+n+q} \Big\} {m+n}$$

where L_i, D_i and U_i are the strictly lower triangular, diagonal and strictly upper triangular parts of J_i, respectively.

Algorithm LLG-eSRIF

V. For each θ_i, $i = 1, \ldots, p$, compute the following quantities:

$$\begin{bmatrix} \dfrac{\partial R_{e,t}^{-T/2}}{\partial \theta_i} & 0 \\ -\dfrac{\partial\left(\tilde{P}_{t+1}^{-T/2} K_{p,t}\right)}{\partial \theta_i} & \dfrac{\partial \tilde{P}_{t+1}^{-T/2}}{\partial \theta_i} \end{bmatrix} = \left[L_i + D_i + U_i^T\right] \tag{12}$$

$$\times \begin{bmatrix} R_{e,t}^{-T/2} & 0 \\ -\tilde{P}_{t+1}^{-T/2} K_{p,t} & \tilde{P}_{t+1}^{-T/2} \end{bmatrix},$$

Algorithm LLG-eSRIF

$$\frac{\partial \bar{e}_t}{\partial \theta_i} = \left[\frac{\partial R_{e,t}^{-T/2}}{\partial \theta_i} - X_i \right] R_{e,t}^{T/2} \bar{e}_t + Y_i F_t \hat{x}_t - L_i, \qquad (13)$$

Algorithm LLG-eSRIF

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$$\frac{\partial S_{t+1}^{(6)}}{\partial \theta_i} = \left[\frac{\partial \left(\tilde{P}_{t+1}^{-T/2} K_{p,t} \right)}{\partial \theta_i} + N_i \right] R_{e,t}^{T/2} \bar{e}_t + \left[\frac{\partial \tilde{P}_{t+1}^{-T/2}}{\partial \theta_i} - V_i \right] F_t \hat{x}_t + K_i. \qquad (14)$$

Algorithm LLG-eSRIF

VI. Finally, we have all values to compute the LLG according to (6):

$$\frac{\partial l_\theta(z_t)}{\partial \theta_i} = -\,\mathbf{tr}\left[R_{e,t}^{1/2} \quad \frac{\partial\left(R_{e,t}^{-1/2}\right)}{\partial \theta_i} \right] + \bar{e}_t^T \quad \frac{\partial \bar{e}_t}{\partial \theta_i} \quad , \; i = \overline{1,p}.$$

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Stages II —V

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- √ The source filtering algorithm, i.e. eSRIF.
- √ The "differentiated" part: Stages II — V.

Thus, the Algorithm LLG-eSRIF is ideal for simultaneous

- √ state estimation
- √ parameter identification.

Algorithm LLG-eSRIF

Remark. Since the matrices in LLG (6) are triangular, only the diagonal elements of $R_{e,t}^{1/2}$ and $\frac{\partial\left(R_{e,t}^{-1/2}\right)}{\partial\theta_i}$ need to be computed. Hence, the Algorithm LLG-eSRIF allows the $m \times m$-matrix inversion of $R_{e,t}$ to be avoided in the evaluation of LLG.

Ill-Conditioned Example Problems

Problem 1 Given:

$$P_0 = \begin{bmatrix} \theta & 0 \\ 0 & \theta \end{bmatrix}, H = \begin{bmatrix} 1, & 0 \end{bmatrix}, R = e^2\theta, \ F = I_2, \ Q = 0,$$

$$G = \begin{bmatrix} 0, & 0 \end{bmatrix}^T, \ 0 < e \ll 1$$

where θ is an unknown parameter, I_2 is an identity 2×2 matrix; to simulate roundoff we assume

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For the $\theta = 1$, this example illustrates the initialization problems [Kaminski P.G., Bryson A.E., Schmidt S.F., 1971] that result when $H_1 \Pi_0 H_1^T + R_1$ is rounded to $H_1 \Pi_0 H_1^T$.

Comparison (Problem 1)

Filter	Exact Answer	Rounded Answer

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'diff' KF	$(P_1)'_\theta = \begin{bmatrix} \frac{e^2}{1+e^2} & 0 \\ 0 & 1 \end{bmatrix}$	$\stackrel{r}{=} \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$

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'diff' IF	$(P_1^{-1})'_\theta = -\begin{bmatrix} \frac{1+e^2}{e^2} & 0 \\ 0 & 1 \end{bmatrix}$	$\stackrel{r}{=} -\begin{bmatrix} \frac{1}{e^2} & 0 \\ 0 & 1 \end{bmatrix}$

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'diff' IF	$(P_1^{-1})'_\theta = - \begin{bmatrix} \frac{1+e^2}{e^2} & 0 \\ 0 & 1 \end{bmatrix}$	$\overset{r}{=} - \begin{bmatrix} \frac{1}{e^2} & 0 \\ 0 & 1 \end{bmatrix}$
LLG-eSRIF	$\left(P_1^{-1/2}\right)'_\theta - \frac{1}{2} \begin{bmatrix} \frac{\sqrt{1+e^2}}{e} & 0 \\ 0 & 1 \end{bmatrix}$	$\overset{r}{=} -\frac{1}{2} \begin{bmatrix} \frac{1}{e} & 0 \\ 0 & 1 \end{bmatrix}$

Ill-Conditioned Example Problems

Problem 2 Given:

$$P_0 = \begin{bmatrix} \theta & 0 \\ 0 & \theta \end{bmatrix}, H = \begin{bmatrix} 1, & 1 \end{bmatrix}, R = e^2\theta,\ F = I_2,\ Q = 0,$$

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Calculate: $(P_1)'_\theta$ at the point $\theta = 1$.

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Comparison (Problem 2)

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'diff' KF	$\frac{1}{2+e^2}\begin{bmatrix} 1+e^2 & -1 \\ -1 & 1+e^2 \end{bmatrix}$	$\frac{1}{2}\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$

Comparison (Problem 2)

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'diff' KF	$\frac{1}{2+e^2}\begin{bmatrix} 1+e^2 & -1 \\ -1 & 1+e^2 \end{bmatrix}$	$\frac{1}{2}\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$
'diff' IF	$-\frac{1}{e^2}\begin{bmatrix} 1+e^2 & 1 \\ 1 & 1+e^2 \end{bmatrix}$	$-\frac{1}{e^2}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$

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'diff' IF	$-\frac{1}{e^2}\begin{bmatrix} 1+e^2 & 1 \\ 1 & 1+e^2 \end{bmatrix}$	$-\frac{1}{e^2}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$
LLG-eSRIF	$-\frac{1}{2}\begin{bmatrix} \sqrt{\frac{2+e^2}{1+e^2}} & \frac{1}{e\sqrt{1+e^2}} \\ 0 & \frac{\sqrt{1+e^2}}{e} \end{bmatrix}$	$-\frac{1}{2}\begin{bmatrix} \sqrt{2} & \frac{1}{e} \\ 0 & \frac{1}{e} \end{bmatrix}$

Numerical Results

Example. Let the test system (1), (2) be defined as follows:

$$x_{t+1} = \begin{bmatrix} 1 & \Delta t \\ 0 & e^{-\Delta t/\tau} \end{bmatrix} x_t + \begin{bmatrix} 0 \\ 1 \end{bmatrix} w_t,$$

$$z_t = \begin{bmatrix} 1 & 0 \end{bmatrix} x_t + v_t$$

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Numerical Results

The negative Log Likelihood Function

The Log Likelihood Gradient

Numerical Results

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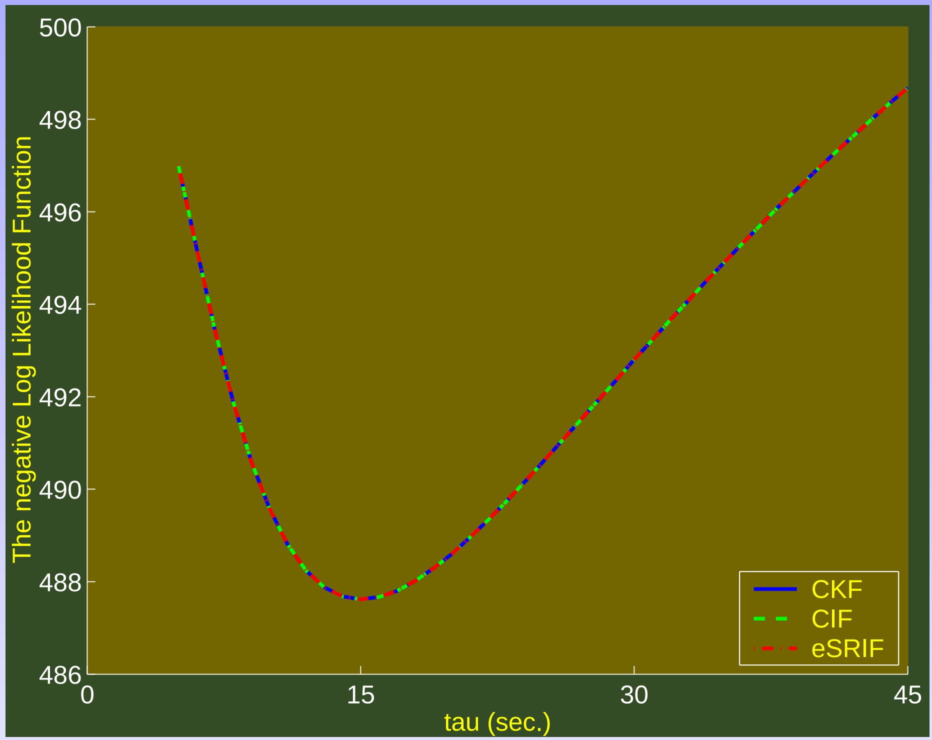
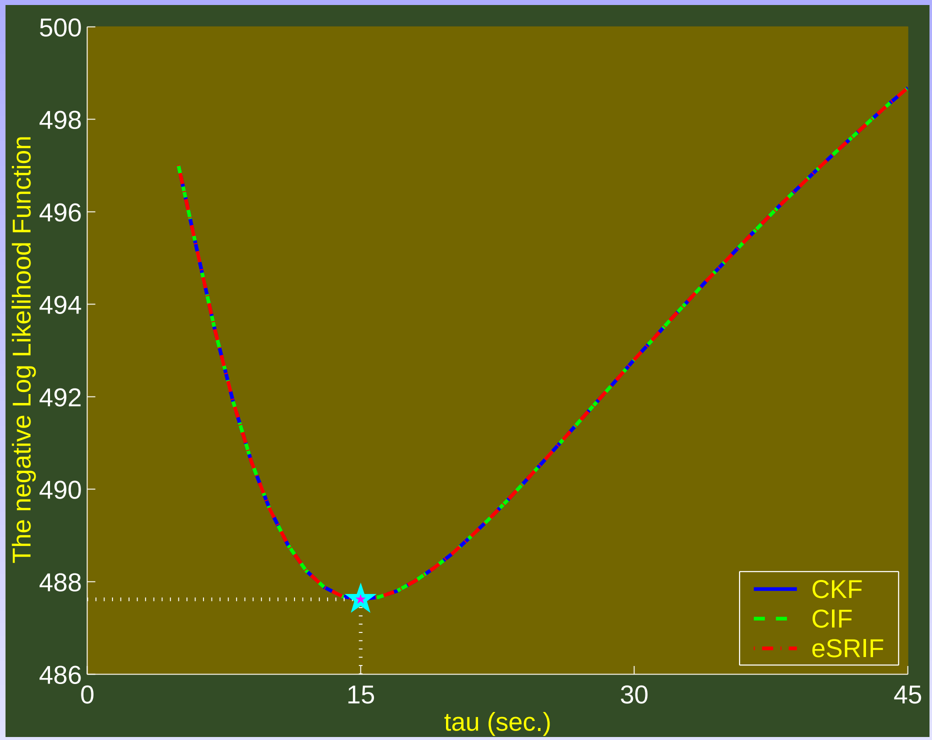
The Log Likelihood Gradient



Numerical Results

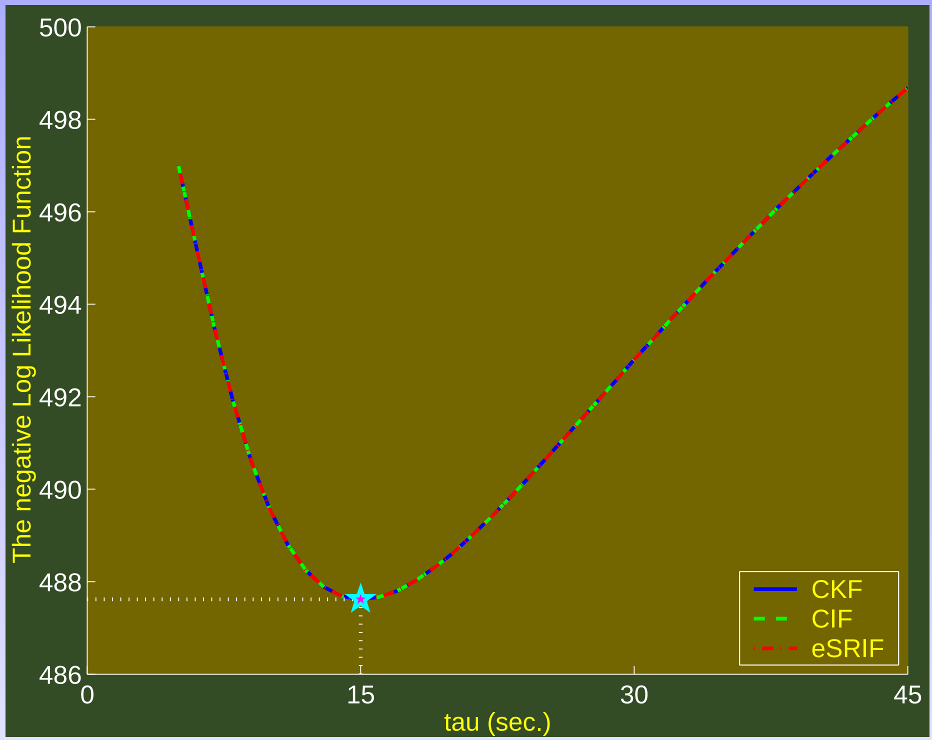
The negative Log Likelihood Function

The Log Likelihood Gradient

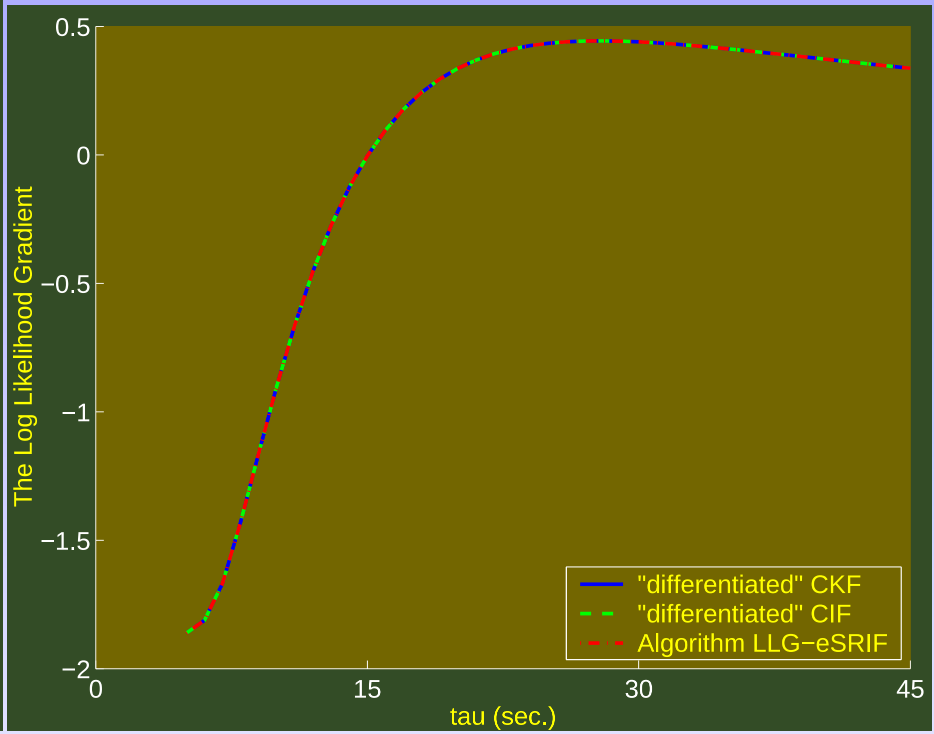


Numerical Results

The negative Log Likelihood Function



The Log Likelihood Gradient



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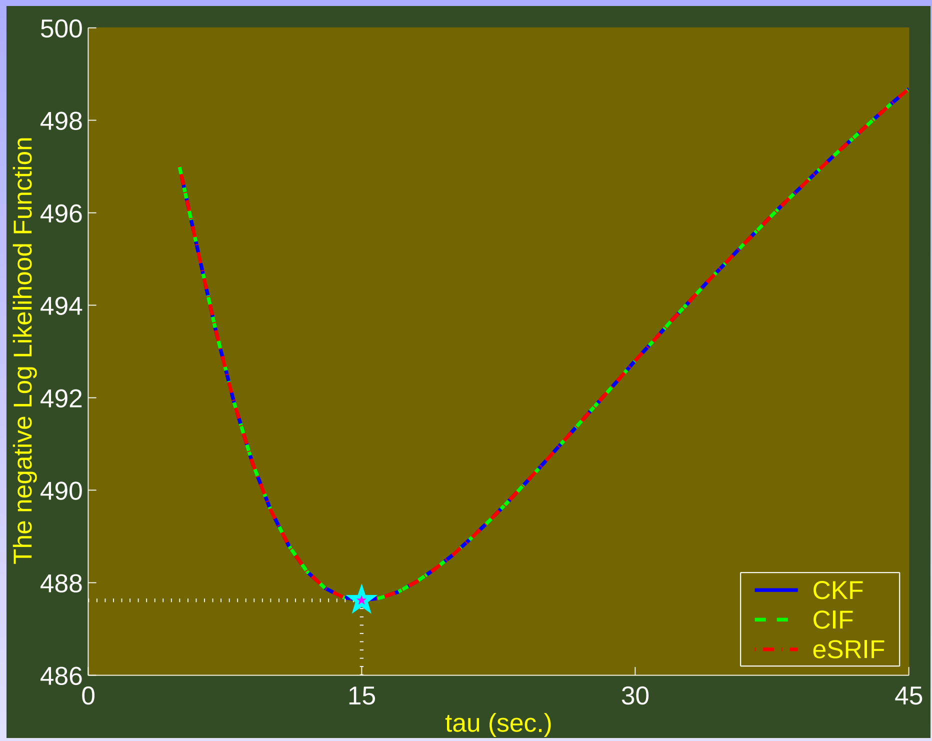

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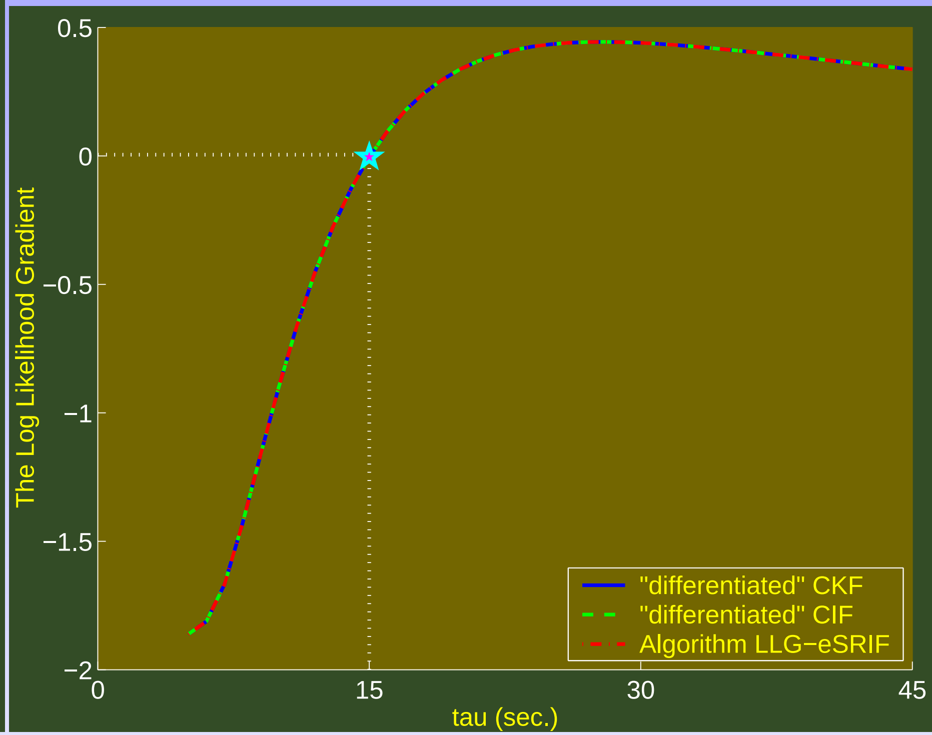

Conclusion

In this paper, the new algorithm for evaluating the Log Likelihood Gradient (score) of linear discrete-time dynamic systems has been developed. The necessary theory has been given and substantiated by the computational experiments. Two ill-conditioned example problems have been constructed to show the superior perfomance of the Algorithm LLG-eSRIF over the conventional approach. All of these are good reasons to use the presented algorithm in practice.

Q & A

Maria Kulikova

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