

Data Fusion of GPS Displacement and Acceleration Response Measurements for Large Scale Bridges

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Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring

Conclusions

Introduction

2 Multi-rate Kalman Filter and Smoother

3 Application to the Monitoring of a Large Scale Bridge

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Introduction

Review of Integration Problem

$$\dot{x} = \int \ddot{x}dt + A$$
$$x = \int \dot{x}dt + At + B$$

- Typical method is to remove the mean A from x(t), and again remove B from x(t)
- Even after this, spurious low frequency error still exists in the displacement
- Could HP filtering data first, however, problems exist:
 - Doesn't work for on-line applications
 - 2 Such filtering needs to be undertaken for zero-phase lag

• b > k @ > < b > k = >

3 Removes significant low frequency components

Introduction

Multi-rate Kalman Filter and Smoothe

Application to Bridge Monitoring



Time-Domain Integration Techniques





Time-Domain Integration Techniques





Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring





Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring

Conclusions

Discrete Time State-Space Model

$$\begin{bmatrix} x_1(k+1)\\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T_a\\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(k)\\ x_2(k) \end{bmatrix} + \begin{bmatrix} T_a^2/2\\ T_a \end{bmatrix} u(k) + \begin{bmatrix} T_a^2/2\\ T_a \end{bmatrix} \eta_a(k)$$
$$z(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(k)\\ x_2(k) \end{bmatrix} + \eta_d(k)$$
.e.

$$\mathbf{x}(k+1) = \mathbf{A}_d \mathbf{x}(k) + \mathbf{B}_d u(k) + \mathbf{w}(k)$$
$$z(k) = \mathbf{H}\mathbf{x}(k) + v(k)$$

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Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring

Conclusions

Kalman Filtering

Time update:

$$\hat{\mathbf{x}}(k+1|k) = \mathbf{A}_d \hat{\mathbf{x}}(k|k) + \mathbf{B}_d u(k)$$

$$\mathbf{P}(k+1|k) = \mathbf{A}_d \mathbf{P}(k|k) \mathbf{A}_d^T + \mathbf{Q}_d$$

Measurement update:

 $\hat{\mathbf{x}}(k+1|k+1) = \hat{\mathbf{x}}(k+1|k) + \mathbf{K}(k+1) [z(k+1) - \mathbf{H}\hat{\mathbf{x}}(k+1|k)]$

P(k+1|k+1) = [I - K(k+1)H]P(k+1|k)

Kalman gain $\mathbf{K}(k+1)$ is given by

 $\mathbf{K}(k+1) = \mathbf{P}(k+1|k)\mathbf{H}^{T} \left[\mathbf{H}\mathbf{P}(k+1|k)\mathbf{H}^{T} + \mathbf{R}_{d}\right]^{-1}$

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Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring

Conclusions

Multi-rate Kalman Filtering

- Assume displacement and acceleration sampling intervals are T_d and T_a respectively, where $T_d/T_a = M$, M is an integer
- Between the times kT_d , only the time update is performed and the optimal estimate is

$$\hat{\mathbf{x}}(k+1|k+1) = \hat{\mathbf{x}}(k+1|k) = \mathbf{A}_{\mathbf{d}}\hat{\mathbf{x}}(k|k) + \mathbf{B}_{\mathbf{d}}u(k)$$

 $\mathbf{P}(k+1|k+1) = \mathbf{P}(k+1|k) = \mathbf{A}_{\mathbf{d}}\mathbf{P}(k|k)\mathbf{A}_{\mathbf{d}}^{T} + \mathbf{Q}_{\mathbf{d}}$

• When displacement measurements are available at times kT_d , both the time update and measurement update are performed

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Introduction

Smoothing

- Multi-rate Kalman Filter and Smoother
- Application to Bridge Monitoring
- Conclusions

- Implement fixed-lag smoothing by using RTS fixed-interval smoothing algorithm
- First filtering up to the current measurement and then sweeping back a fixed number of steps *S* with the RTS algorithm. If the number of backward steps is small, then the estimation is near "on-line"
- The smoothed estimates $\hat{\mathbf{X}}(k|N)$ over (0, N) is given by $\hat{\mathbf{X}}(k|N) = \hat{\mathbf{X}}(k|k) + \mathbf{F}(k)[\hat{\mathbf{X}}(k+1|N) - \hat{\mathbf{X}}(k+1|k)]$ where smoothing gain $\mathbf{F}(k)$ is given by $\mathbf{F}(k) = \mathbf{P}(k|k)\mathbf{A_d}^T \mathbf{P}^{-1}(k+1|k), \quad k = N-1, N-2, \dots, 0$



Application to the Monitoring of a Large Scale Bridge

Introduction

Multi-rate Kalman Filter and Smoother

Application to Bridge Monitoring

Conclusions

Dynamic monitoring

- A large scale suspension bridge located near New York City has a main span of 1298 meters
- Displacement and acceleration were monitored during the 2004 NYC Marathon
- The sampling frequency of the acceleration measurement is 100 Hz
- The sampling frequency of the displacement measurement is 5 Hz, i.e., the Nyquist frequency is 2.5 Hz



Acceleration Measurements from the Bridge

Introduction

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Displacement Estimates



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Displacement Estimates

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Velocity Estimates



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Comparison of PSD for Measured and Smoothed Displacement





Conclusions

Introduction

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Application to Bridge Monitoring

Conclusions

- The multi-rate Kalman filter and smoother provide a robust method to estimate displacement and velocity responses for large scale bridges.
- The multi-rate estimating aspect permits a relatively low sampling rate for GPS displacement measurements





