



Approach to the Problem of Localization with data loss

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June 30, 2009

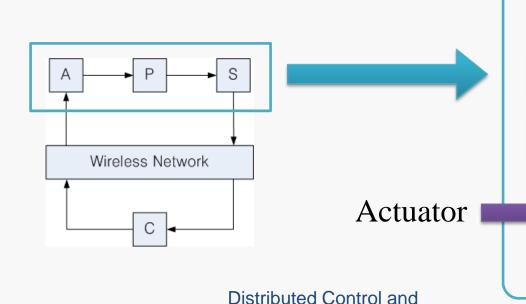




Problem of Ubiquitous Localization Network

Sensor

- Imperfections in single control loop include
 - Delay and jitter
 - Bandwidth limitation
 - Data loss and bit errors
 - Outages and disconnection



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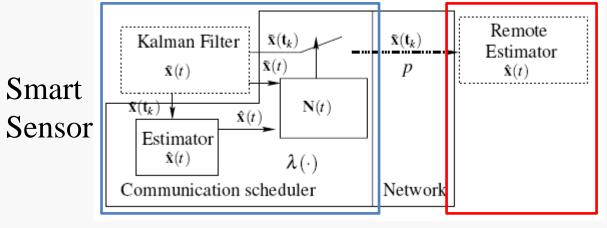
Localization with Data Loss

- Keyword
 - Lossy Network
 - Sample Rate Varying
 - Data Dropout
 - Data Loss
 - Intermittent Observations
 - Dropping Packets
- Implication Definition
 - Estimation with considering mobile target, sample rate varying, and distributed system.





 A communication pattern: a communication scheduler on the smart sensor and a lossy network



$$\dot{\mathbf{x}} = A\mathbf{x} + \mathbf{w}$$
$$\mathbf{y} = C\mathbf{x} + \mathbf{v}$$

- Authors model data sending times as jumps of an integer random process (Poisson process).
- The intermittent time can be determined by controlled random processes (Poisson process) so as to use system dynamics information.

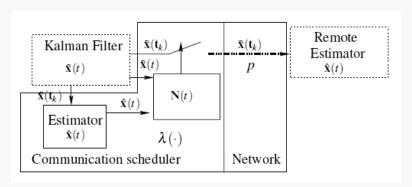




 An integer-valued random measure N(t) is constructed by Possion process mechanism.

$$\Pr\left[\mathbf{N}(t+dt) - \lim_{s \to t^{-}} \mathbf{N}(s) = 1\right] = \Lambda\left(\mathcal{I}(t^{-})\right) dt$$

- $\Lambda(\mathscr{I}(t^-)) dt$ is probability of sending data.
- P is probability of dropping packets.







The communication pattern models the communication scheduling and the network uncertainties, as in Fig. 4. Specifically, we consider two patterns:

- 1) The communication scheduler is driven by a Poisson process with a constant Poisson rate λ , and the packets get lost with probability p, $0 \le p < 1$. Since packet loss is independent of the Poisson process, data arrives at the remote estimator according to another Poisson process with rate $(1-p)\lambda$.
- The communication scheduler is driven by an integer-valued process with jump intensity $\lambda(\tilde{\mathbf{e}}^-)$, and the packets get lost with probability p. In this case, the effective intensity becomes $(1-p)\lambda(\tilde{\mathbf{e}}^-)$.

For analysis purposes, the data loss probability p does not add complexity. From now on, λ or $\lambda(\tilde{\mathbf{e}}^-)$ refers to the intensity that data are *received* on the remote estimator.





• γ is constant Poisson rate

Consider a communication scheduler that is driven by a Poisson process with a rate $\gamma > 0$. Define

$$\gamma_{2m} := 2m \max{\Re[\operatorname{Eig}(A)]}.$$

Theorem 1. Let the estimation error $\hat{\mathbf{e}}$ be defined as in (1), (3)-(5), in which the time sequence \mathbf{t}_k , $k \geq 0$, is generated by a Poisson process with a nonnegative rate γ . For any $m \geq 1$, if $\gamma > \gamma_{2m}$, $\mathrm{E}[(\hat{\mathbf{e}}(t)'\hat{\mathbf{e}}(t))^m]$ is bounded, $\forall t \geq 0$, and if $\gamma < \gamma_{2m}$, $\lim_{t \to \infty} \mathrm{E}[(\hat{\mathbf{e}}(t)'\hat{\mathbf{e}}(t))^m] \to \infty$.

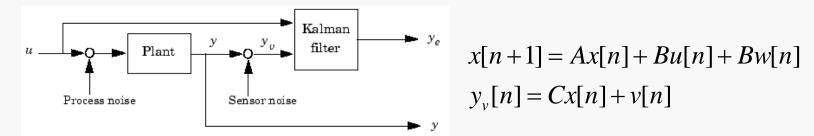
- γ_{2m} is a tight bound.
- In the first pattern, Estimation error covariance is bounded if P is larger than tight bound.





Time-Varying Kalman Filter

- In the related papers, raw measurements are sent to the remote TVKF via a lossy network.
- Plant state and measurement equations



- Time update
 - State estimation uncertainty is considered by every time update.

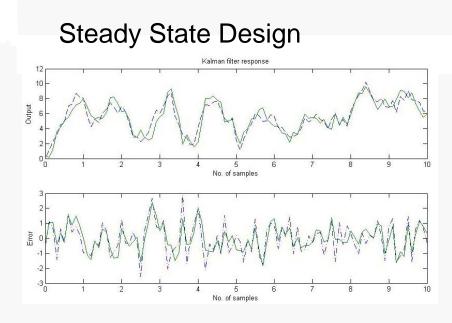
$$\hat{x}[n+1|n] = A\hat{x}[n|n] + Bu[n]$$

$$P[n+1|n] = AP[n|n]A^{T} + BQ[n]B^{T}$$

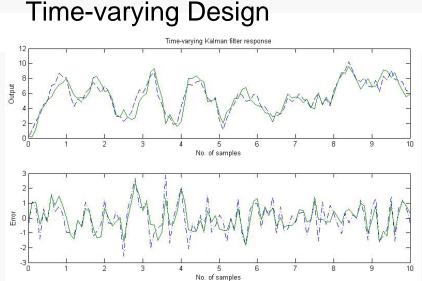




Time-Varying Kalman Filter



0.7232



Error Covariance

0.7234

The value of TVKF is close to the value obtained for the steady state design.