A sequential Bayesian approach to distributed source localization

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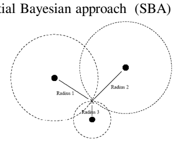
Introduction

- A Wireless Sensor Network consists of numerous , inexpensive tiny sensors that can sense their environment
- Their resources are constrained: limited battery supply, limited computational and storage capabilities. They may lack regular maintenance
- They can cooperate among themselves and distributed processing is the central dogma
- Applications include wildlife habitat monitoring, tracking autonomous vehicles, sensing hazardous environments
- Source localization is an important task . It is concerned with the Estimation of source location based on some sensory measurements of the source such as acoustic energy
- We consider source localization based on acoustic energy measurements in a distributed manner (in-network computations)
- Sequential Bayesian approach (SBA) is an attractive choice



Model

$$y_j \sim N\left(A[(\theta_1 - x_1)^2 + (\theta_2 - x_2)^2]^{-1}, \sigma^2\right)$$

- y_j — Received signal strength at the j^{th} sensor (observed)
- A — Acoustic energy of the source (assumed known)
- $\begin{bmatrix}\theta_1 \\ \theta_2\end{bmatrix}$ — Source location (to be estimated)
- $\begin{bmatrix}x_{j,1} \\ x_{j,2}\end{bmatrix}$ — j^{th} sensor location (known)
- σ^2 — Measurement variance (assumed known)

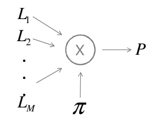
Goal:

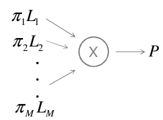
Estimate the source location based on the 'N' received signal strength measurements obtained at each of the M sensors as accurately as possible, expending minimum resources

Methods

Independent Likelihood

$$P \propto \pi \prod_{j=1}^{M} L_j$$



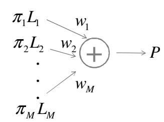


Independent Opinion

$$P \propto \prod_{j=1}^{M} L_j \pi_j$$

Linear Opinion

$$P \propto \sum_{j=1}^{M} w_j L_j \pi_j$$



Sequential Implementation

- Approximation: $P_j \approx N(\mu_j, \Sigma_j)$
- Use adaptive quadrature methods to solve $\int g(\theta) L_j(\theta) \pi_j(\theta)\, d\theta$
- Independent Likelihood: $P_j \propto P_{j-1} L_j$
- Independent Opinion:

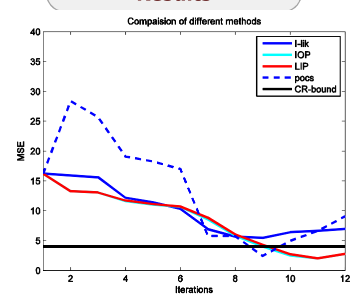
$$P_j^s \propto P_{j-1}^s P_j$$
$$(\Sigma_j^s)^{-1} = (\Sigma_{j-1}^s)^{-1} + (\Sigma_{j-1})^{-1}$$
$$\mu_j^s = \Sigma_j^s[(\Sigma_{j-1}^s)^{-1} \mu_{j-1}^s + (\Sigma_{j-1})^{-1} \mu_j]$$

- Linear Opinion:

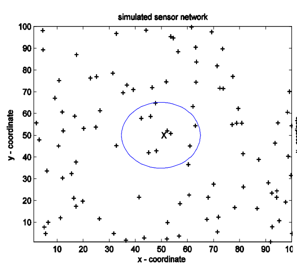
$$P_j^s \propto w P_{j-1}^s + (1-w) P_j$$
$$\mu_j^s = w \mu_{j-1}^s + (1-w)\mu_j]$$
$$\Sigma_j^s = w(\Sigma_{j-1}^s + \mu_{j-1}^s (\mu_{j-1}^s)^T) + (1-w)(\Sigma_j + \mu_{j-1}\mu_{j-1}^T) - \mu_j^s (\mu_j^s)^T$$

- Estimate: $\hat{\theta} = E_{P_j^s}(.)$

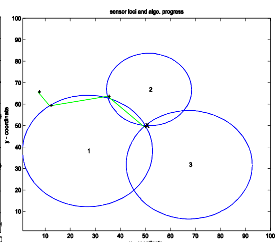
Results



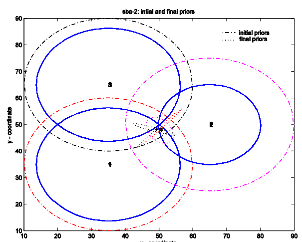
Simulations



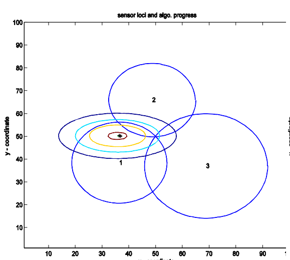
A Sensor Network

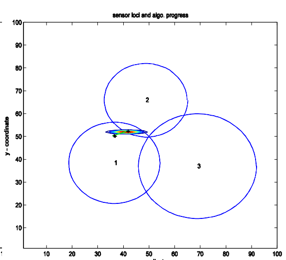


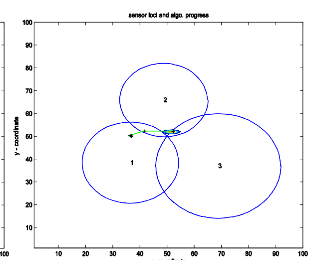
convex projection/
Iterated least-squares



Priors in SBA







Localization in-progress

Conclusions

- Exploits node (sensor) location
- Uses informative prior
- Independent Likelihood can be seen as Kalman-filter counter parts
- Flexibility in handling different types of priors
- Independent Opinion pool and Linear opinion pool perform very similarly
- Perform better than classical methods (MSE is smaller than Cramer-Rao bound)
- Robust to outliers
- Low computational cost (vs MCMC)
- Node failure models can be integrated

Future work

- Approximations to reduce communication cost
- Extend for moving sources
- Relative node localization
- Sources with unknown energy
- Missing data

References

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