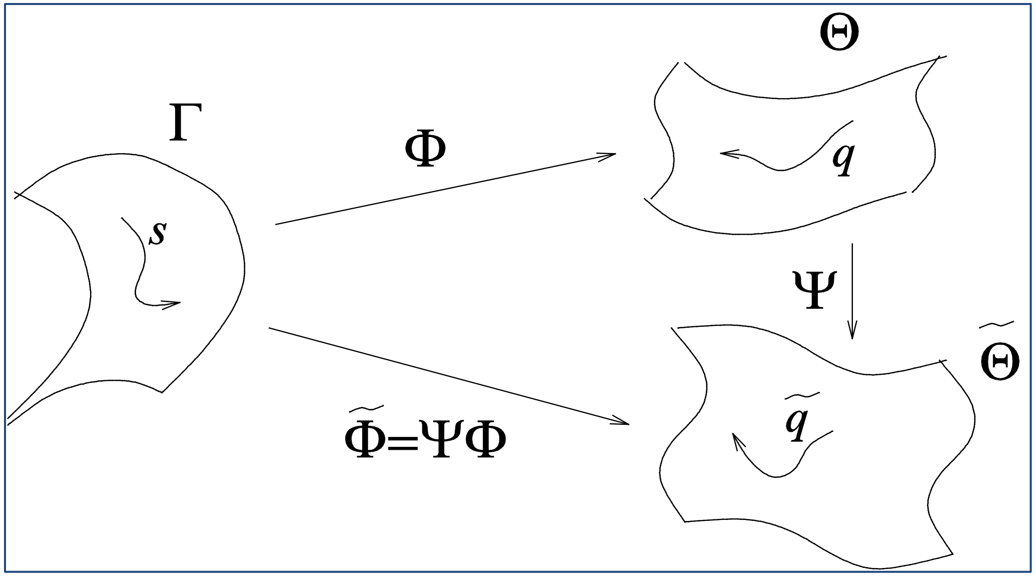
# Information-geometric VoI in Sensor Planning

*Co-PIs: A. Hero and D. Cochran*

- **Motivating question**: Can VoI with respect to a sensing objective be described geometrically via Rao's differential geometric view of statistical manifolds?




## Summary

1. Smooth adjustment of sensor parameters defines a curve in a statistical manifold $\Theta$
2. Information change can be quantified by measures on $\Theta$
3. Sensor planning can be carried out wrt geometry defined by informational objectives

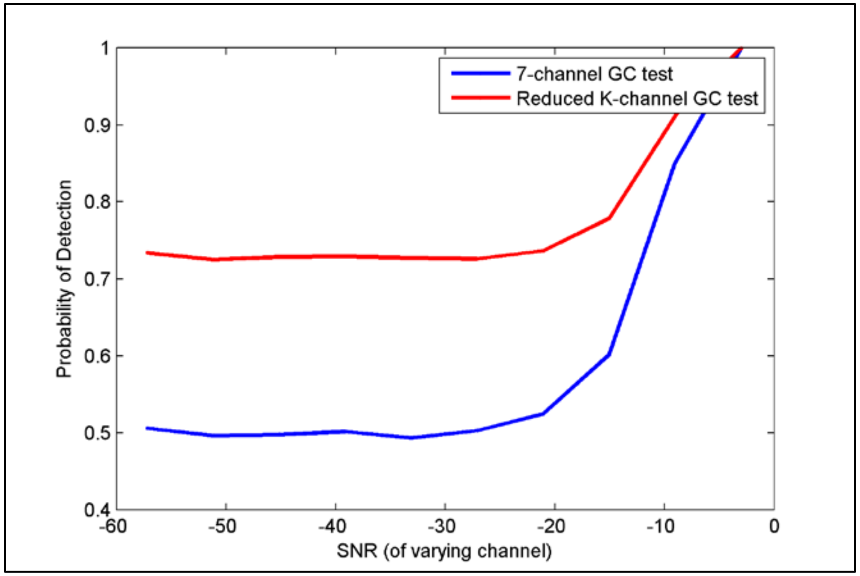
- **Relevance**: The VoI of a sequence of sensor control actions with respect to an objective may be characterized by geometric properties of curves on a statistical manifold
- **Collaborator**: B. Sadler (ARL)

[1] D. Cochran, A. Hero, ``Information-driven sensor planning," GlobalSIP, December 2013

# Analyze-Fuse vs. Fuse-Analyze

*Co-PIs: R. Nadakuditi and D. Cochran*

- **Motivating question**: Can censoring weak channels prior to application of standard multi-channel detectors improve overall detection performance?




**Summary**

1. Work at UM under this MURI shows that "analysis before fusion" often begets performance gains [1]
2. Multi-channel detection algorithms developed at ASU are well matched to the models underpinning these results
3. Good initial results suggest combining with entropic surrogation [2]

- **Relevance**: Pertains to the VoI in weak channels relative to typical downstream fusion and inference
- **Student**: L. Crider (ASU)

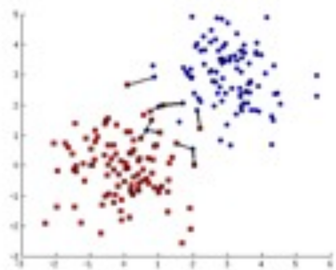

[1] R. R. Nadakuditi, IEEE SSP Workshop, 2011

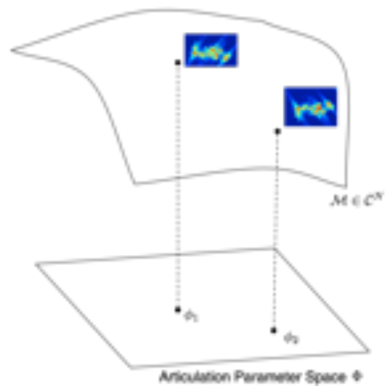
[2] K. Beaudet, L. Crider, D. Cochran, SPIE Defense, Security, and Sensing Conference, 2013

# Non-parametric methods for estimation of Fisher Information for Target Manifolds (Hero,Ertin)

VOI

Student: D. Teng



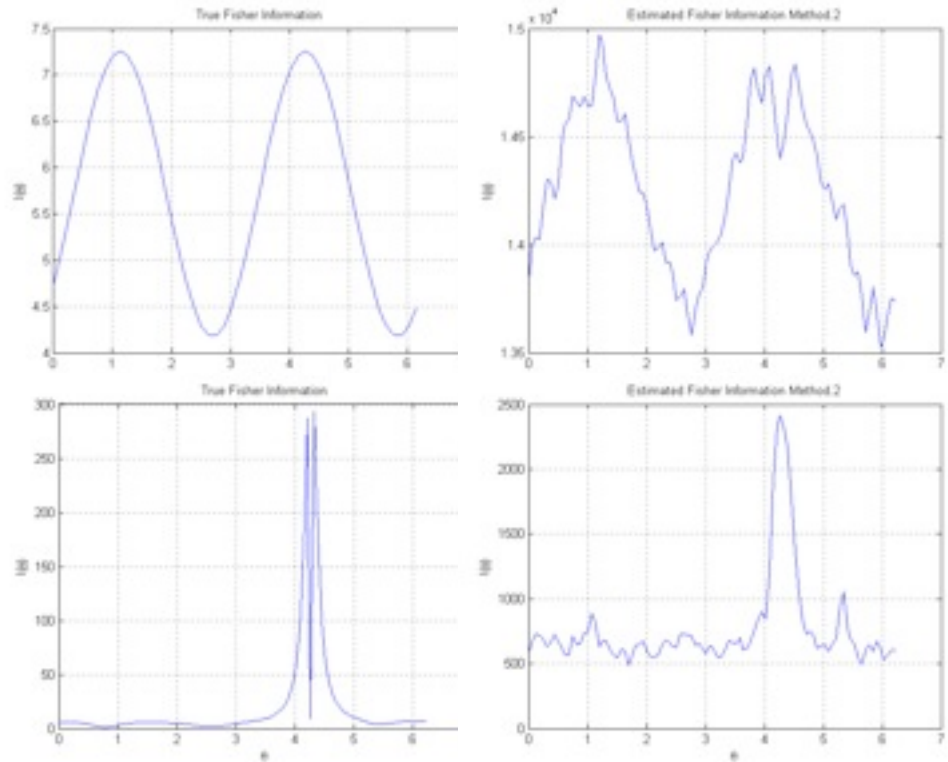



Fisher Information reveals the amount of information an observation contains about the unknown parameter in the probability density function.

$$\mathcal{I}(\theta) = \int (\frac{\partial}{\partial\theta} \log f(x;\theta))^2 f(x;\theta) \mathrm{d}x$$
$$= \int (\frac{\partial f(x;\theta)}{\partial\theta})^2 \frac{1}{f(x;\theta)} \mathrm{d}x$$

We propose to use MST approximation to $\alpha$ divergence and it's second derivative to estimate Fisher Information

$$\mathcal{I}(\theta_0) = \alpha^{-1} \frac{\partial^2 D_\alpha(\theta \| \theta_0)}{\partial \theta^2}|_{\theta=\theta_0}$$




Next, we plan to consider Henze-Penrose Affinity

$$A(f,g) = \int \frac{fg}{\epsilon f + (1-\epsilon) g}$$

and consider the link to the Fisher Information

$$1 - A(f_\theta, f_{\theta+u}) = \epsilon(1-\epsilon)\, u^T F_\theta u + o(\|u\|^2)$$

VOI

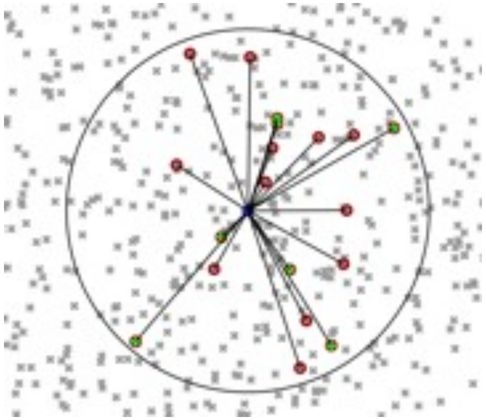
# Kronecker Factorization of Interference Covariance for decentralized tracking (Hero/Ertin)

$$\Sigma^{-1}_{vec(\mathbb{N})} \approx \sum_{i=1}^{r} \hat{\Sigma}_T(i) \otimes \hat{\Sigma}_S(i)$$

Distributed Detection and Tracking of deterministic signals in random noise with spatio-temporal correlation

$$LLR(Y,\theta) = \sum_{i=1}^{r}\sum_{j=1}^{n}[Y^k_{\hat{\Sigma}_T}(i)]_{(j,:)}[S^k_{\hat{\Sigma}_S}(\vec{\theta},i)]_{(:,j)} - c(\vec{\theta})$$

We consider a distributed computing strategy for likelihood based on Kronecker factorization of the spatio-temporal covariance matrix.



•Require storage of are independent of the observation, we can preconfigure "whitened signatures" in each sensor.

•Each sensor only require its own observation to perform the calculation of local statistics.

•Fusion center require only the calculated local statistics from each sensor to make final decision

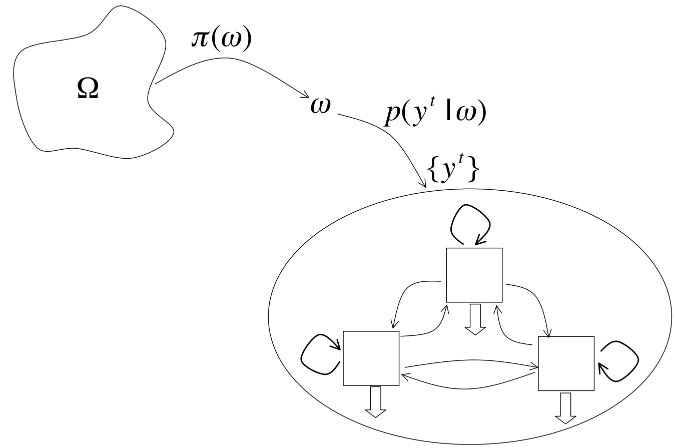
•Data flow between sensor and fusion center is reduced significantly.

VOI

# Confirmation Bias and Divergent Beliefs Human Subjects: Role of Quantized Beliefs (Ertin/Yu)


Effect of quantized beliefs on human interpretation and collection of information

Study parallels between human decision making processes and optimal Bayesian update and experimental design strategies with quantized beliefs




- Empirical Questions:
  - Can we design experiments to test evidence of quantized beliefs and measure granularity of quantization?
  - Gender, Culture Differences?
- Theoretical Questions:
  - Collaboration strategies between people with different quantization structures
  - Machine fusion algorithms for learning exploiting quantization structure in human reports

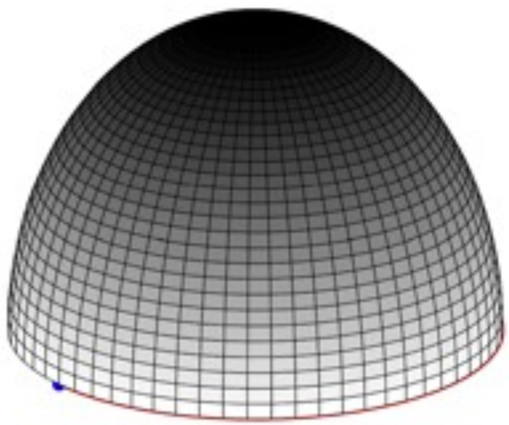
VOI

# Bayesian subspace tracking (Cochran/Ertin/Moses)

Recently, fast subspace identification and tracking methods have been proposed based on incremental updates with point estimates without an associated uncertainty measure [Balzano-Nowak-He, Chi-Eldar-Calderbank]

Computationally demanding Sequential Monte Carlo methods have been proposed earlier [Srivastava]

Howard-Cochran-Sirianunpiboon recently consider Bayesian subspace detection problems. They proposed a parametrization of the Grassmannian for closed form integration over nonuniformative prior using Laplace approximation.



Real grassmanian $G_{1,3}$

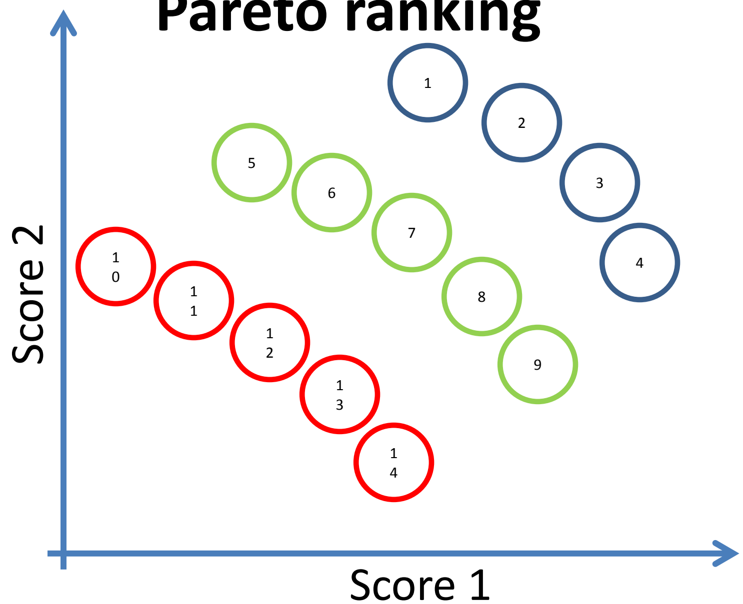
- Formulation of simple parametric prior on Grassmannian using smooth parametrization employed by HCS.
- Closed-form integration and finding closest posterior in the parametric family
- Track point estimate and concentration around the estimate

# Learning how to rank many objects

## M. Jordan and A. Hero

- **Motivating question**: can we learn to rank objects in large database based on a persons' rankings of just a few objects?

**Pareto ranking**




**Main questions**

1. What rank orders are identifiable from incomplete observations? [1]
2. Can one simplify the problem by PDE relaxations? Partial rankings using Hamilton-Jacobi equations[2]
3. What are minimax convergence rates of numerical PDE solns to ranking problems?

- **Relevance**: predicting human ranking behavior is important for human-in-the-loop systems.
- **Students**: J. Duchi (UCB) and J. Calder (UM)


[1] Duchi etal, "Asymptotics of ranking," 2013

[2] Calder etal, "A Hamilton-Jacobi equation for…non-dominated sorting," 2013.

# Heterogeneous Sensor Allocation in Unknown Environment

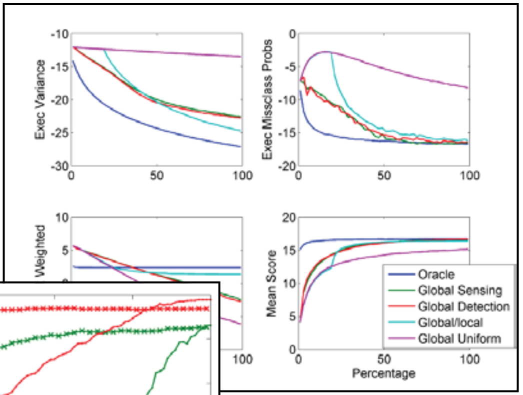
B. Mu, G. Newstadt, D. Wei, A. Hero, J. How

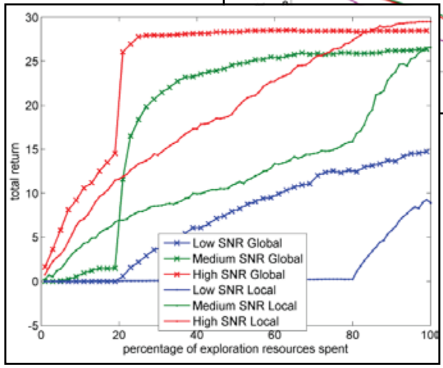
- **Motivating question**: how can you allocate limited heterogeneous resources to detect targets and maximize execution mission return?

## Main questions

1. What are useful objective functions for jointly detecting/ classifying/tracking targets with noisy measurements?
2. What are the performance tradeoffs among
   a) Locally adaptive sensors (i.e., UAVs)
   b) Globally adaptive sensors (i.e., agile wide-area sensors)
   c) Mixture of globally uniform/ locally adaptive sensors
3. How does performance compare to oracle policies?

Comparison among policies and objectives →




← Tradeoff in exploration/ exploitation

- **Relevance**: Sensor management in uncertain environments can lead to large gains in both uncertainty reduction and mission value.
- **Students/Postdocs**: B. Mu (MIT), G. Newstadt (UM), D. Wei (UM)

[1] Mu etal, “Value-of-information aware active task assignment,” 2013
[2] Wei and Hero, “Multistage adaptive estimation of sparse signals,” 2013.