

# Journal Watch: TSP-June. 2014

June 14, 2014

**Paper Title:** Distributed State Estimation With Dimension Reduction Preprocessing

**Authors:** Hang Ma, Yu-HanYang, Yan Chen, K. J. Ray Liu, and Qi Wang

**Affiliations:** University of Maryland, USA

- Main theme: Big Data. Paper questions if the data can always be processed efficiently
- Raw measurements preprocessed- compressed and later used for estimation. Goal: Making data concise enough but preserve as much information as possible
- Proposed: Block-wise preprocessing of data and estimation
- Joint design of the preprocessor and the estimator: Each block responsible for compressing its data and estimating desired quantities
- Results: Derive bounds on dimension reduction. Provide convergence guarantee along with performance guarantees.

**Paper Title:** Consensus-based Distributed Particle Filtering with Distributed Proposal Adaptation

**Authors:** Ondrej Hlinka, Franz Hlawatsch and Petar M. Djuric

**Affiliations:** Vienna University of Technology, Vienna; Stony Brook University, NY

- Goal: To develop a DPF for sequential estimation of global state information by incorporating observations at all sensors in a decentralized wireless sensor network
- Technique: uses only local computations at individual sensors and local communications (neighbor)
- Contribution 1: Likelihood consensus scheme for distributed calculations of the joint likelihood function is generalized to arbitrary local likelihood function
- Contribution 2: Consensus based distributed method for adapting the proposal densities used by local particle filters
- Demonstrate that there is significant performance improvement since all measurements are used, significant decrease in the number of particles

**Paper Title:** Forest Sparsity for Multi-Channel Compressive Sensing

**Authors:** Chen Chen, Yeqing Li, and Junzhou Huang

**Affiliations:** University of Texas, Arlington

- Model considered:  $\mathbf{A}\Phi^{-1}\theta = \mathbf{b}$  ( $\Phi$ : Standard Basis such as Wavelet or Fourier) where  $\theta$  is approximately sparse. For  $k$  sparse data, the number of measurements required:  $\mathcal{O}(k + k \log\{\frac{N}{k}\})$
- Number of measurements for  $T$  group-sparse vectors:  $\mathcal{O}(Tk + k \log\{\frac{N}{k}\})$
- Number of measurements for  $T$  tree-sparse vectors:  $\mathcal{O}(Tk + T \log\{\frac{N}{k}\})$
- Derive results for forest-sparse vectors: pMRI, Multi-contrast MRI, multi-spectral image reconstruction etc.
- Result: Number of measurements for  $T$  forest-sparse vectors:  $\mathcal{O}(Tk + \log\{\frac{N}{k}\})$

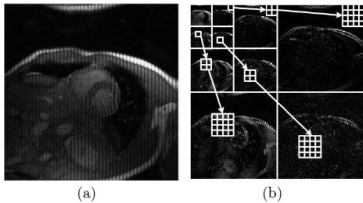


Fig. 1: Wavelet quadtree structure: a) A cardiac MR  
sponding tree structure of the wavelet coefficients.

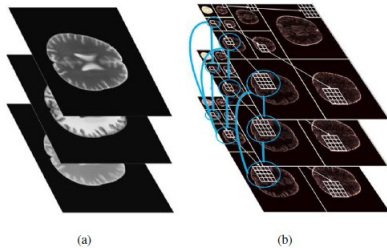


Figure: Tree Sparsity

Figure: Forest Sparsity



**Paper Title:** Bayesian Group-Sparse Modeling and Variational Inference

**Authors:** S. Derin Babacan, Shinichi Nakajima, and Minh N. Do

**Affiliations:** UIUC IL; Nikon Corporation, Tokyo

- Proposes a general class of multi-variate priors for group-sparse (block-sparse) modeling in the Bayesian framework
- Derives estimation procedures within these priors using variational inference for fully Bayesian estimation
- Result: Constructed prior is a normal variance mixture formulation. Hierarchical construction of a general signal prior for group-sparse models- several existing priors can be derived
- Advantages of a generalized construction: exploring different group-sparse models, analyze their connections and sparsity-enforcing properties
- Extensions- multiple measurements, intra-group correlations, overlapping groups

**Paper Title:** Sequential Distributed Detection in Energy-Constrained Wireless Sensor Networks

**Authors:** Yasin Yilmaz, and Xiaodong Wang

**Affiliations:** Columbia University, NY

- Problem: Handling random overshoots in a distributed sensor network using sequential distributed detection (level-triggered sampling)
- Propose to encode the random overshoot into time delay between sampling time and transmission time
- Results pertain to order-1 and order-2 optimality of proposed schemes

## Other Papers

- SUMIS: Near-Optimal Soft-In Soft-Out MIMO Detection With Low and Fixed Complexity: M. irki and E. G. Larsson
- Fixed-Lag Smoothing for Bayes Optimal Knowledge Exploitation in Target Tracking :F. Papi, M. Bocquel, M. Podt, and Y. Boers
- Approximate Subspace-Based Iterative Adaptive Approach for Fast Two-Dimensional Spectral Estimation: W. Sun, H. C. So, Y. Chen, L.-T. Huang, and L. Huang
- Optimal Energy Allocation for Energy Harvesting Transmitters With Hybrid Energy Storage and Processing Cost: O. Ozel, K. Shahzad, and S. Ulukus
- An Adaptive Approach to Learn Overcomplete Dictionaries With Efficient Numbers of Elements: M. Marsousi, K. Abhari, P. Babyn, and J. Alirezaie
- Deterministic Construction of Sparse Sensing Matrices via Finite Geometry: S. Li and G. Ge