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Novel Distributed Wavelet Transforms and Routing Algorithms for Efficient Data Gathering in Sensor Webs

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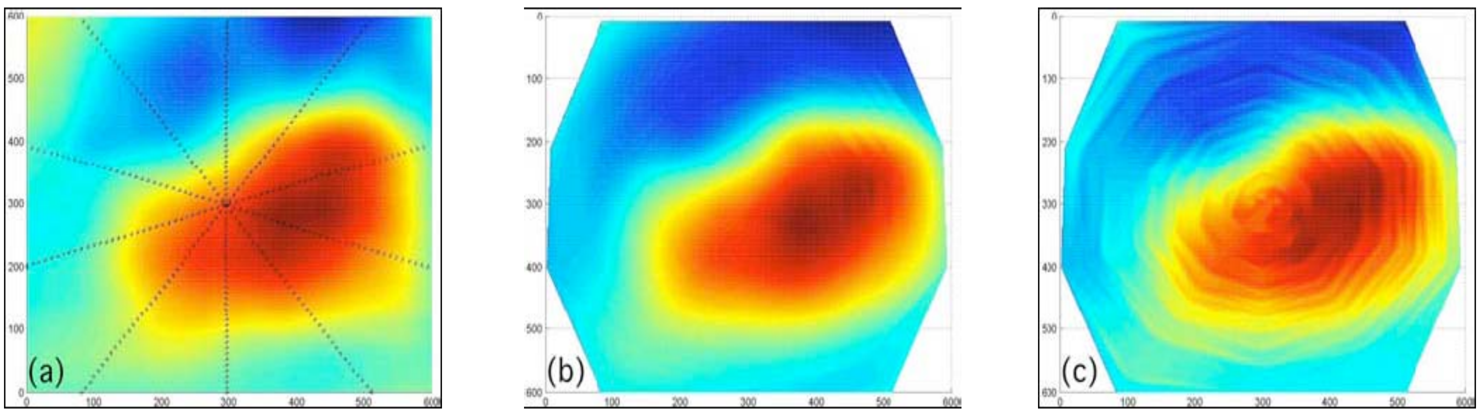
Objectives

- Design algorithms that minimize energy consumption by compressing correlated measurements as data is routed to the sink

- Enable nodes to reconfigure the network automatically by taking into account variations in node characteristics



Example of a 2D field measured by a sensor web: (a) true field, and reconstructed field using (b) distributed wavelets or (c) quantized data with the same energy consumption as in (b).

Approach

- Develop data compression algorithms that exploit data correlation
  - Entropy coding, filter optimization, path merging, joint compression and routing, temporal coding, compressed sensing
- Implement advances in networking and routing
  - Node selection, network initialization, routing optimization, link quality robustness, inclusion of broadcast nodes, and automatic reconfigurability
- Test these new capabilities
  - In the lab, and in a sensor web of about 100 nodes in an outdoor realistic environment for an extended period of time

Work to Date

- Data compression algorithms
  - Entropy coding, path merging, joint compression and routing, temporal coding, compressed sensing
- Advances in networking and routing
  - Node selection, routing optimization, inclusion of broadcasts
- In lab experiments
  - Preliminary experimental results for small, in lab networks

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Presentation Outline

1. **Related pre-AIST work**
2. **Data Compression**
   - Entropy Coding
   - Spatio-temporal transforms and coding
   - Spatio-temporal subsampling
   - Compressed sensing
   - Tree based 2D wavelet transforms
3. **Networking**
   - Joint routing and transform optimization
   - Inclusion of broadcast nodes
   - Erasure Correcting Codes
4. **Mote Implementation**
   - In lab implementation (tree based 2D wavelet)

Pre-AIST Joint Routing and Compression Technique (Ciancio, Ortega, Pattem, Krishnamachari – USC)

- Unidirectional 5/3 lifting transform along routing paths [1]
- Heuristic for dealing with merged paths for 2-D networks [2]
- Transform optimization per path

- Pros:
  - Unidirectional computation (no backward transmissions)
  - Path-wise transform optimization
  - Practical alternative to existing methods

- Cons:
  - Overhead from heuristic merging technique (not critically sampled)
  - Only exploits path-wise correlation
  - Optimization only path-wise, does not extend to 2D transforms

[1]. A Ciancio and A. Ortega, "A distributed wavelet compression algorithm for wireless multihop sensor networks using lifting", ICASSP'04.

[2]. A. Ciancio, S. Pattem, A. Ortega, B. Krishnamachari, "Energy-efficient data representation and routing for wireless sensor networks based on a distributed wavelet compression algorithm", IPSN'06.

Entropy Coding
(A. Kiely, M. Klimesh, H. Xie - JPL)

Goal: Use entropy coding (data compression) to minimize cost of transmitting values needed to compute a Discrete Wavelet Transform (DWT) in the sensor web. This reduces the energy required to achieve a given level of quality in the reconstructed data.

Motivation: Combined distributed DWT and entropy coding enables joint compression of the data generated by different nodes as the information accumulates over the routing path.

Results:

- Devised a general purpose entropy coding method for our transforms
- Details found in our NSTC 07 Paper [1]

[1]. G. Shen, et al, “A distributed wavelet approach for efficient information representation and data gathering in sensor webs ”, NSTC’07.

Spatio-Temporal Coding (H. Xie – JPL)

Goal:

- Combine temporal and spatial coding to minimize overall data transmission for further energy reduction
- Consider both temporal and spatial correlation for node selection

Motivation:

- Most existing work focuses on *spatial correlations* only
- Data collected at each node exhibits high temporal correlation
- Temporal processing is local and far cheaper than spatial compression, and so should be fully exploited to minimize the transmission cost

Two notable exceptions:

- Lightweight Temporal Coding [1]
- Distributed Predictive Coding [2]

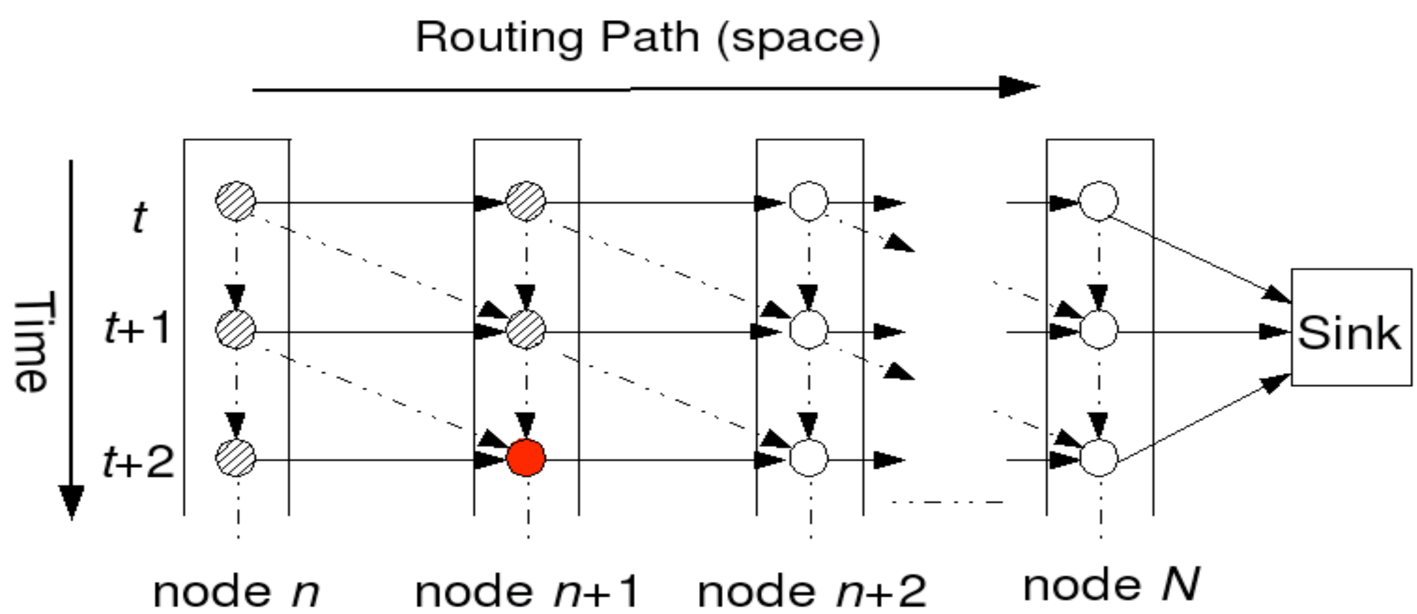
[1]. T. Schoellhammer, B. Greenstein, E. Osterweil, M. Wimbrow, and D. Estrin, “Lightweight temporal compression of microclimate datasets”, LCN'04.

[2]. A. Saxena and K. Rose, “Distributed predictive coding for spatio-temporally correlated sources”, ISIT 2007.

Spatio-Temporal Coding

Key Observation:

- In data aggregation-based compression, data is transmitted through multiple hops along a predefined routing path, and compressed jointly it flows towards the sink
- To encode data at a node for a given time instance, we can use all the information from the current node / time instance along with data from previous nodes / time instances **(see figure below)**



Information flow along a 1D path in an aggregation-based data transmission system.

Spatio-Temporal Coding

Assumptions

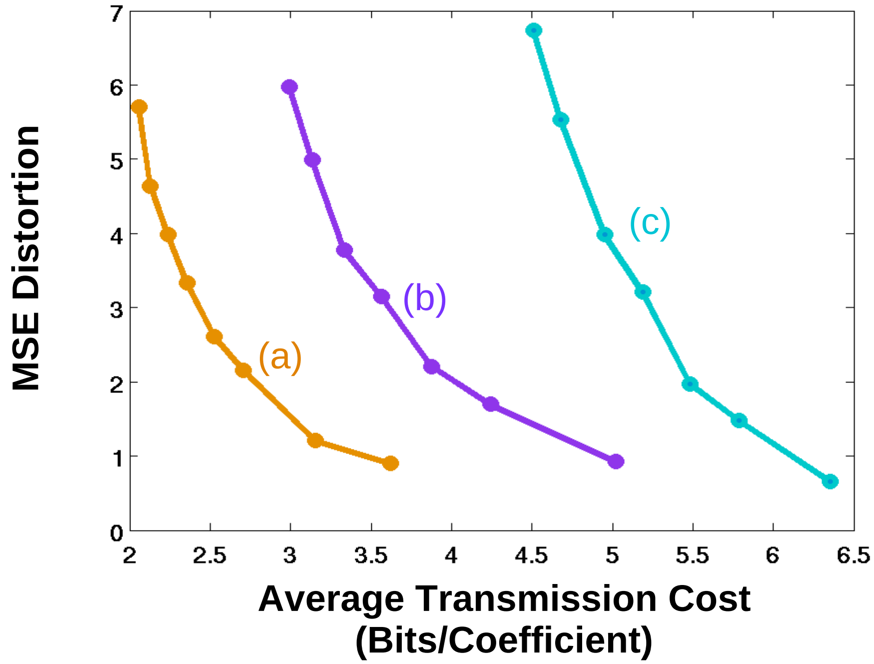
- Spatial routing path is established
- Latency introduced by local temporal processing is tolerable

Approaches

- **Separable wavelet transform**
- Perform a single stage 3/5 reversible integer DWT on data sequence at each node to exploit temporal redundancy
- Perform spatial compression using distributed wavelet transform and entropy coding
- **Adaptive filtering (work in progress)**
- Each sample value is predicted from the historical data
- The difference between the estimate and the actual value is encoded and transmitted
- The estimation error is also used to update the filter weights

Example: 10-bit source data as quantized version of 2D second-order Auto Regressive process with poles at $0.99e^{\pm j\pi/64}$

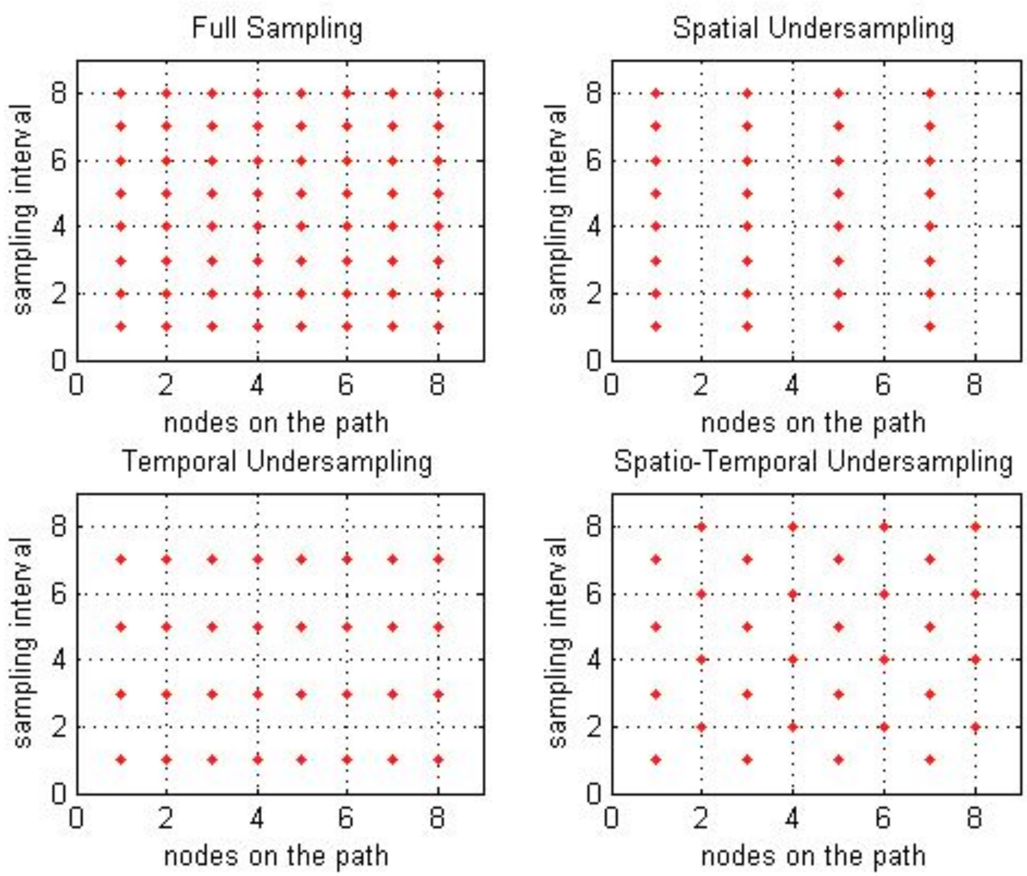
Rate-Distortion Performance



This rate-distortion graph shows the benefit of (a) Spatio-temporal coding using 2D wavelet transform and (b) Spatial compression only, compared to the baseline approach of (c) entropy coding quantized sample differences (spatial only).

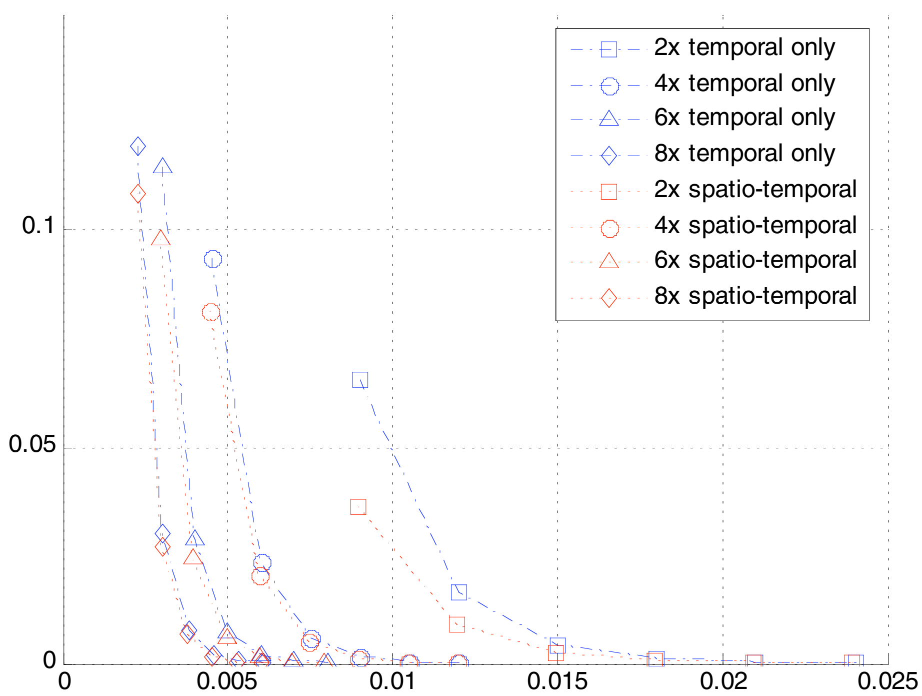
Spatio-Temporal Sampling (S. Lee and A. Ortega – USC)

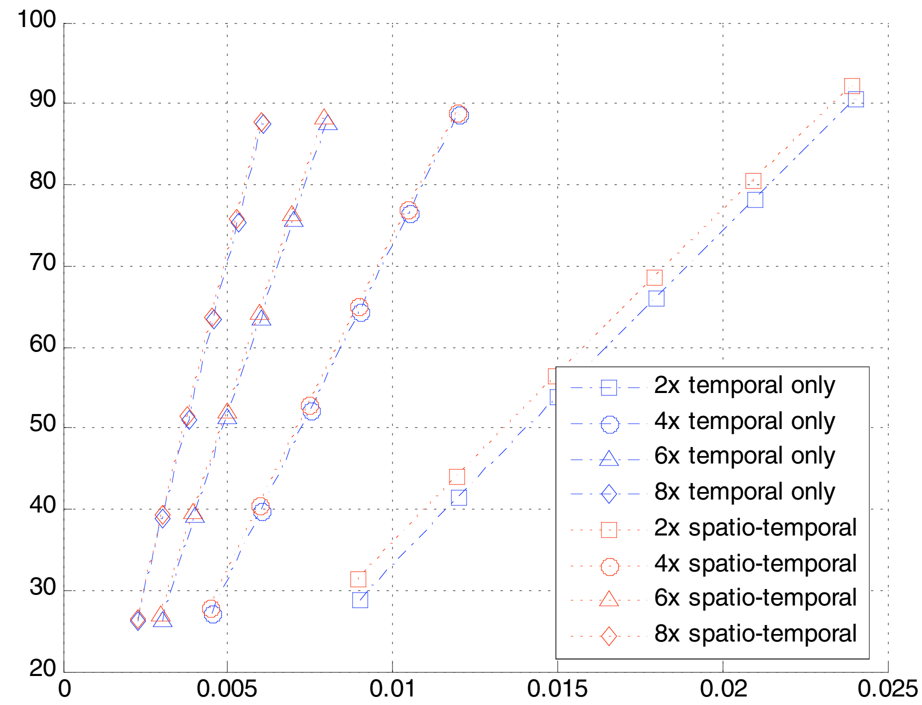
- Spatio-temporal sampling patterns may lead to lower transmission cost for same quality
- Benefits depend on spectral characteristics of data



Spatio-Temporal Sampling

Results – Real World Data : VTB data [1]





There is max 2.6dB gain vs. temporal-only case in cost-PSNR sense.

[1] Jeongyeup Paek, Omprakash Gnawali Ki-Young Jang, Daniel Nishimura, Ramesh Govindan, John Caffrey, Mazen Wahbeh, Sami Masri, A Programmable Wireless Sensing System for Structural Monitoring, In: 4th World Conference on Structural Control and Monitoring(4WCSCM), San Diego, CA, July 2006

Transforms and Routing

- **Problem definition:**
  - What data should be gathered from each node, how should it be aggregated and transferred to the fusion node, how should it be reconstructed

- **Two major approaches:**
  - Traditional techniques use data from all nodes, and reconstruct snapshots of the state of field
    a. Can handle any type of data
    b. Exact reconstruction up to quantization error
  - We are exploring new techniques (i.e., compressed sensing, spatio-temporal sampling), where:
    a. Some form of undersampling is used
    b. Exact reconstruction only for classes of signals (sparse, band-limited)

Compressed Sensing for Sensor Networks
(S. Lee, S. Pattem, B. Krishnamachari, A. Ortega)

Overview:

- Compressed Sensing (CS) is a technique capable of representing an N-length signal (which is K-sparse) using only M << N measurements

Goal:

- Design measurement matrices that lead to efficient routing while also maintaining a high level of reconstruction quality

Experimental Observations:

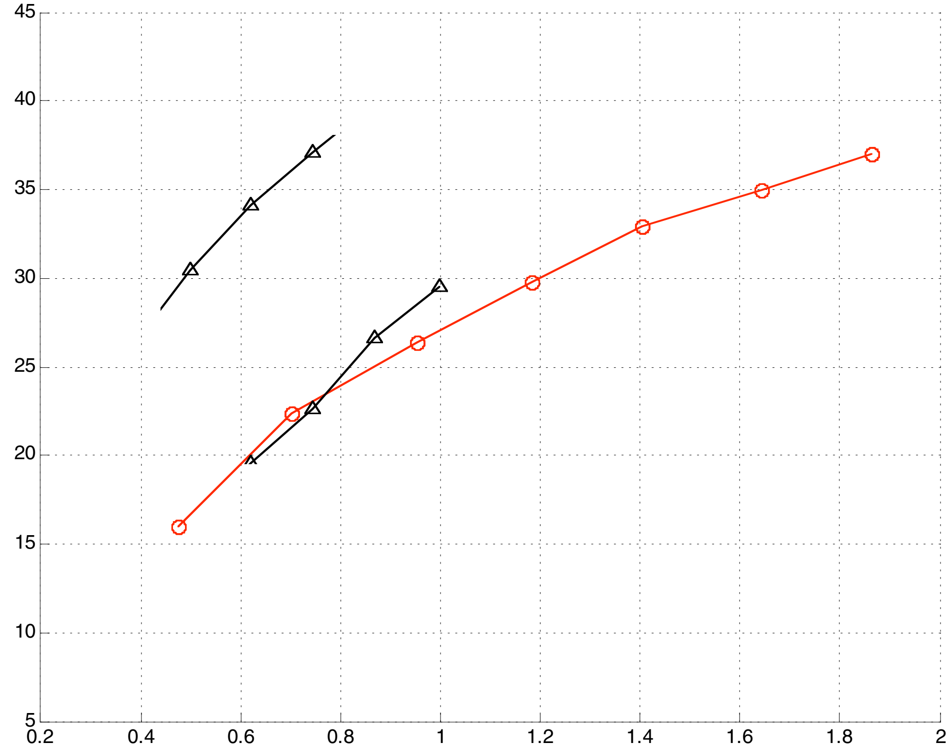
- Our previous method [1] designed routing/measurement matrices that are highly “incoherent” with the assumed signal basis (Fourier, Haar, etc)
  - However, correlation between coherence and reconstruction quality is low

- Spatial downsampling (DS) with CS is more efficient both in terms of reconstruction quality and energy cost

[1]. G. Shen, et al, “A distributed wavelet approach for efficient information representation and data gathering in sensor webs ”, NSTC’07.

Compressed Sensing for Sensor Networks

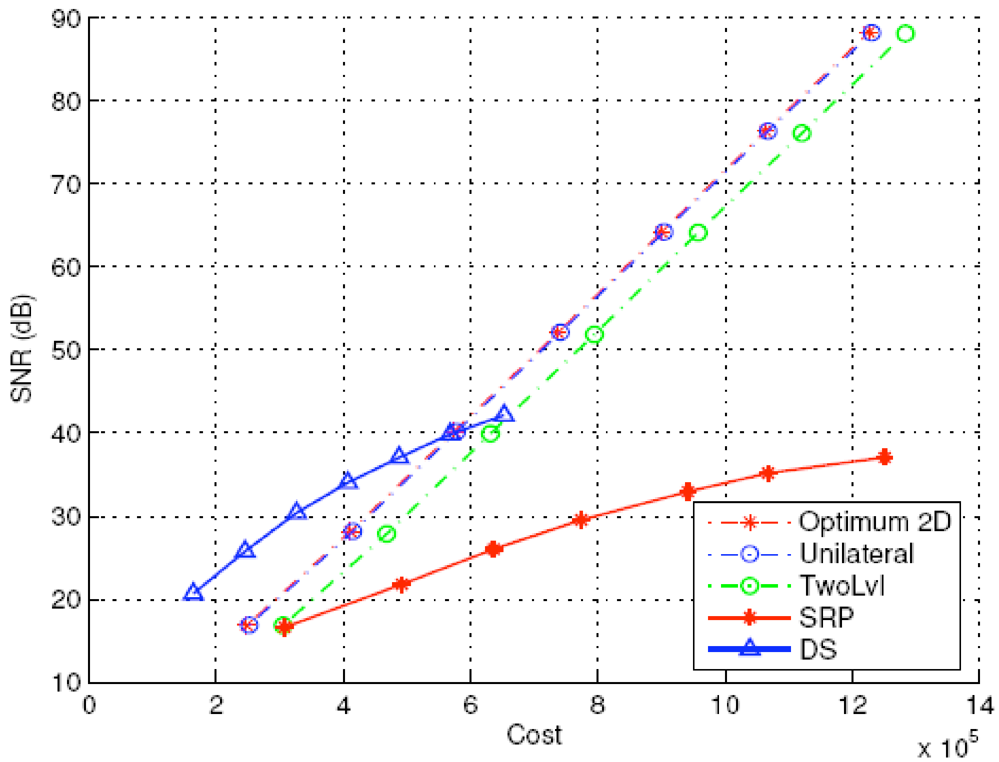
- DS consumes less energy for the same level of reconstruction quality than DRP and SRP
  - AR data and DCT / Multi-level Haar basis
  - DS projection is highly incoherent with DCT basis and Haar basis.



Energy ratio vs. SNR of DS and SRP projections for AR data.
DRP is out of range due to very high energy cost.

Compressed Sensing for Sensor Networks

- CS with DS projection can provide a higher SNR at the same cost for the low SNR region than 2D wavelet transform.
  - AR data and DCT basis for CS
  - CS has limited achievable SNR (unless the number of projections increases significantly.)



CS with DCT basis vs. 2D wavelet transform.

Compressed Sensing for Sensor Networks

- **Conclusions**
  - Coherence is not accurate enough indicator for the reconstruction to consider as design metric for measurement matrix
  - Downsampling with CS is efficient in terms of reconstruction quality and energy consumption

- **Future work**
  - Extending to general topologies (currently using square grid)

Tree Based 2D Wavelet Transforms (G. Shen, A. Ortega - USC)

Goal: Design and optimize a 2D transform

- Invertible, critically sampled, and unidirectional
- Exploits 2D correlation (not just path-wise, 1D correlation)
- Lifting filters arbitrary to permit filter optimization

Motivation:

- More de-correlation w/ 2D transform than path-wise transform [1]
- Existing 2D transforms require backwards transmissions [2]

Our Proposed Method:

- Lifting transform along an arbitrary tree [3]
- Transform optimization via dynamic programming along a tree

[1]. A Ciancio and A. Ortega, "A distributed wavelet compression algorithm for wireless multihop sensor networks using lifting", ICASSP'04.

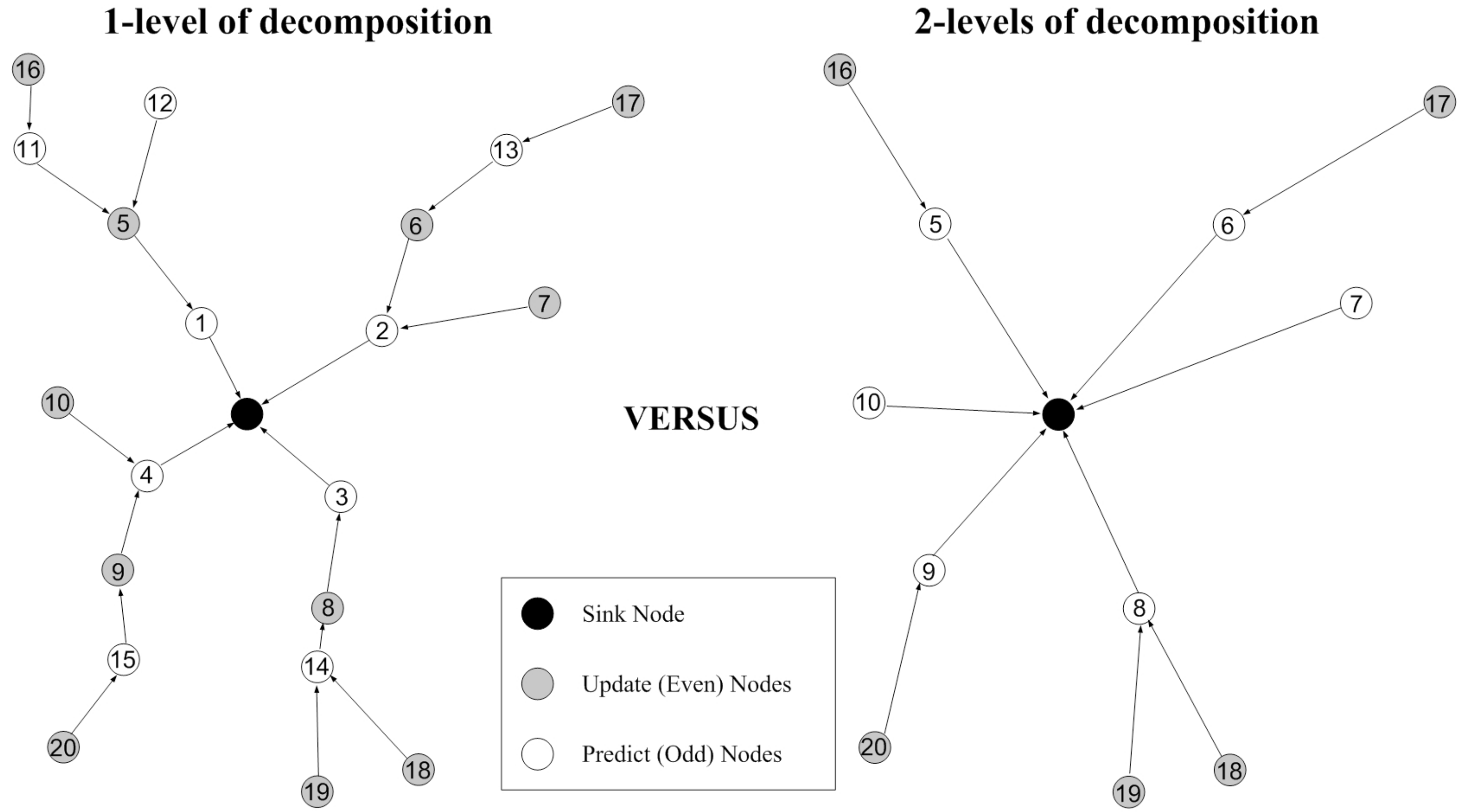
[2]. R. Wagner, H. Choi, R. Baraniuk, V. Delouille, "Distributed wavelet transform for irregular sensor network grids", IEEE SSP'05.

[3]. G. Shen and A. Ortega, "Optimized distributed 2D transforms for irregularly sampled sensor network grids using wavelet lifting", ICASSP'08.

Tree Based 2D Wavelet Transforms

Lifting Transform Design (Split Design)

- Split sensors into **even** and **odd** nodes according to depth in tree
- Sequence of splitting trees across multi-levels (derive T_j from T_{j-1})



Tree Based 2D Wavelet Transforms

Lifting Transform Design (Filter Design)

- Can be computed in a variety of ways (planar regression, etc)
- We use simple averaging and smoothing ideas

$$\mathbf{p}_{n,j}(m) = -\frac{1}{|\mathcal{C}_{n,j}|+1} \text{ for each } m \in \mathcal{C}_{n,j} \cup \{\rho_{n,j}\}$$

$$\mathbf{u}_{m,j}(k) = \frac{1}{2(|\mathcal{C}_{m,j}|+1)} \text{ for each } k \in \mathcal{C}_{m,j} \cup \{\rho_{m,j}\}$$

Children of m in splitting tree T_j

Parent of m in splitting tree T_j

Lifting Transform Computation

- Explicitly separate terms for parents and children

$$d_{m,j} = s_{m,j-1} + \sum_{k \in \mathcal{C}_{m,j}} \mathbf{p}_{m,j}(k) s_{k,j-1} + \mathbf{p}_{m,j}(\rho_{m,j}) s_{\rho_{m,j},j-1}$$

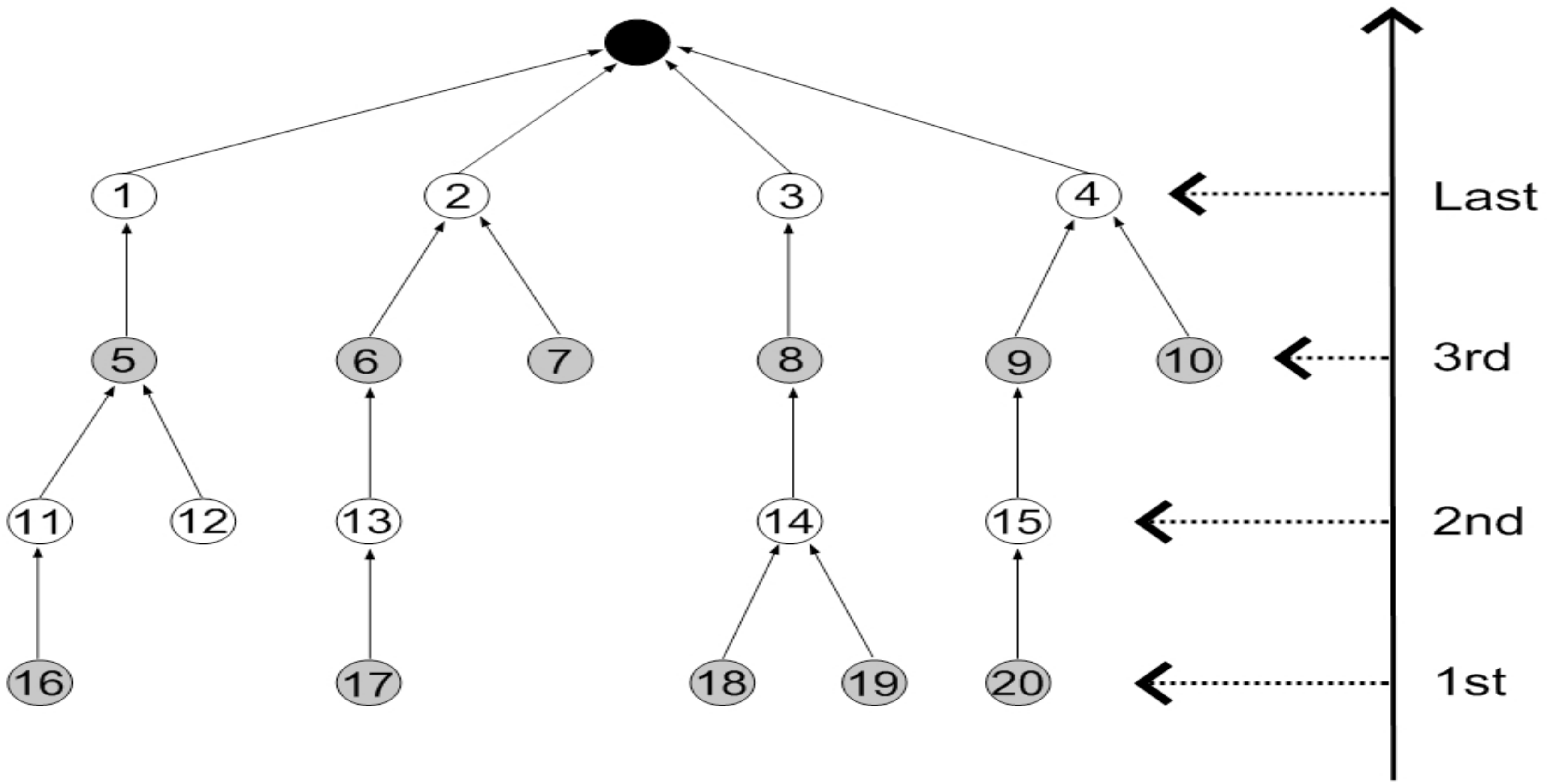
$$s_{n,j} = s_{n,j-1} + \sum_{m \in \mathcal{C}_{n,j}} \mathbf{u}_{n,j}(m) d_{m,j} + \mathbf{u}_{n,j}(\rho_{n,j}) d_{\rho_{n,j},j}$$

- Permits *unidirectional* transform computation (no backwards tx)

Optimized Unidirectional 2D Transforms on Arbitrary Trees

Unidirectional Transform Computation

Equivalent Tree w/ Unidirectional Computation



Tree Based 2D Wavelet Transforms

Transform Optimization (Cost Minimization for Fixed Distortion)

- Formulate as a *Forward Dynamic Program*
- Define the following quantities:
  - $S = \{1, 2, \ldots, J\}$ the set of coding schemes (levels of decomposition)
  - $t_{i,j}^{n}$ the cost to transition from level i at n to level j at parent of n
  - $\mathcal{J}_j(n)$ the optimal cost to arrive at level j at node n from its children
- We then have:

$$\mathcal{J}_j(n) = \min_{\{i_m \in S : m \in K_n\}} \left\{ \sum_{m=1}^{M_n} t_{i_m,j}^{c_{n,m}} + \mathcal{J}_{i_m}(c_{n,m}) \right\}$$

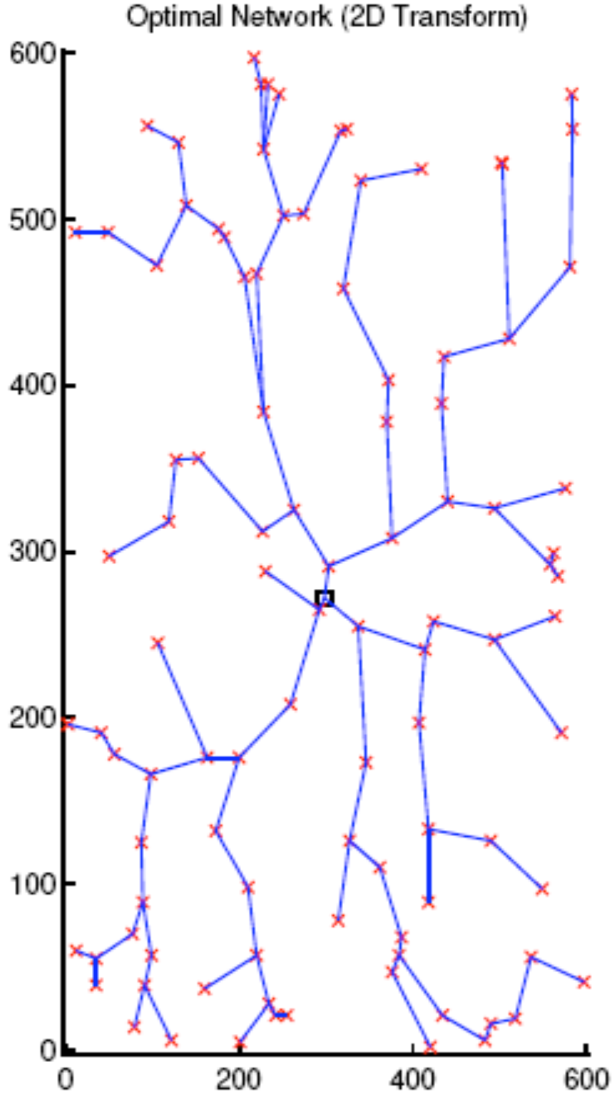
- The optimal solution is found using the results of Algorithm 1

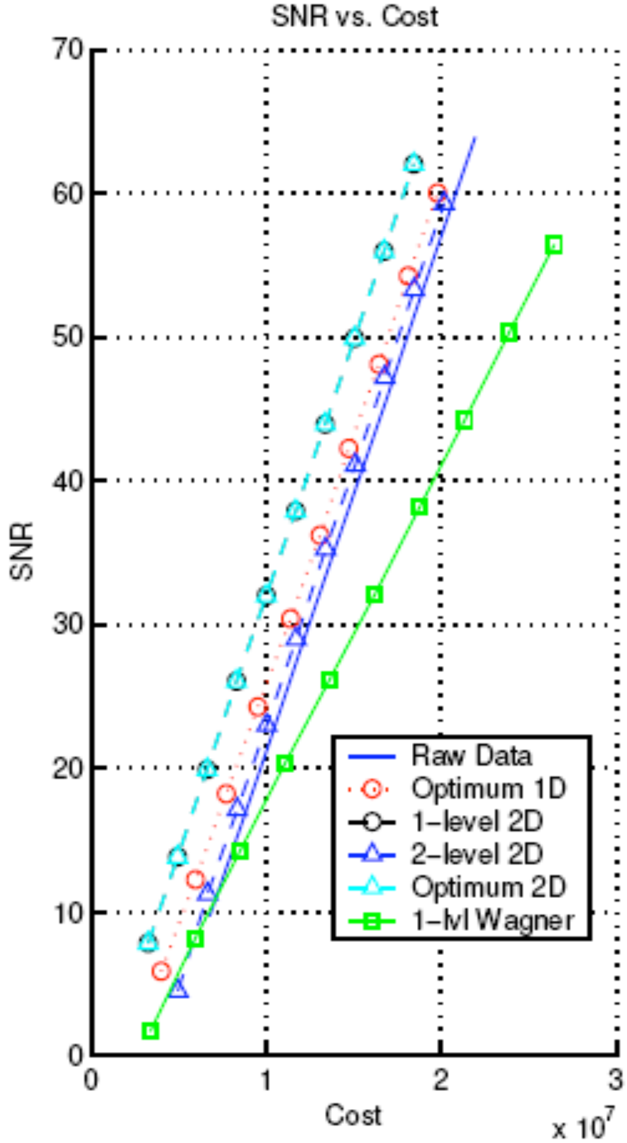
Algorithm 1 Compute Optimal Costs

1: **for** $k = \max(\text{depth}) : -1 : 1$ **do**
2: $\quad \mathcal{I}_k = \{m \in \mathcal{I} : \text{depth}(m) = k\}$
3: $\quad$ **for** each $n \in \mathcal{I}_k$ **do**
4: $\quad\quad$ **for** each $j \in S_n$ **do**
5: $\quad\quad\quad$ Compute $\mathcal{J}_j(n)$ and $\mathbf{t}(n, j) = (i_1^*, i_2^*, \ldots, i_{M_n}^*)$
6: $\quad\quad$ **end for**
7: $\quad$ **end for**
8: **end for**

Tree Based 2D Wavelet Transforms

Results (Highly Correlated AR-2 Data, 100 Nodes)





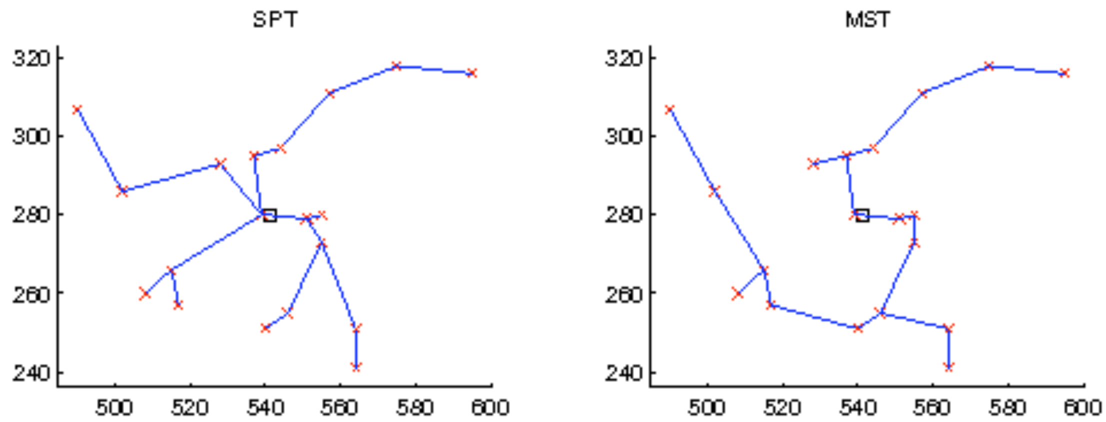
Joint 2D Transform and Routing Optimization (G. Shen, A. Ortega - USC)

Goal:

- Find routing trees that jointly optimize routing and compression

Key Observations:

- Shortest path routing trees (SPT) provide minimum total distance, not always minimum per hop distance (for higher correlation)
- Hurts coding efficiency if data along tree is not well correlated
- Per hop correlation is higher along minimum spanning tree (MST)
- Tradeoff between low total multi-hop dist. and high per hop corr.



Joint 2D Transform and Routing Optimization

Optimization Problem:

- Find a spanning tree that minimizes total cost for a given distortion

Our Proposed Method:

- Find an optimized combination of trees, i.e., MST and SPT [1]
- Useful approximation to true optimal tree
    - Number of spanning trees is very large (Matrix-Tree Theorem)
    - **Can exploit tradeoff by combining min. cost routing (SPT) with high data correlation tree (correlation- based MST)**

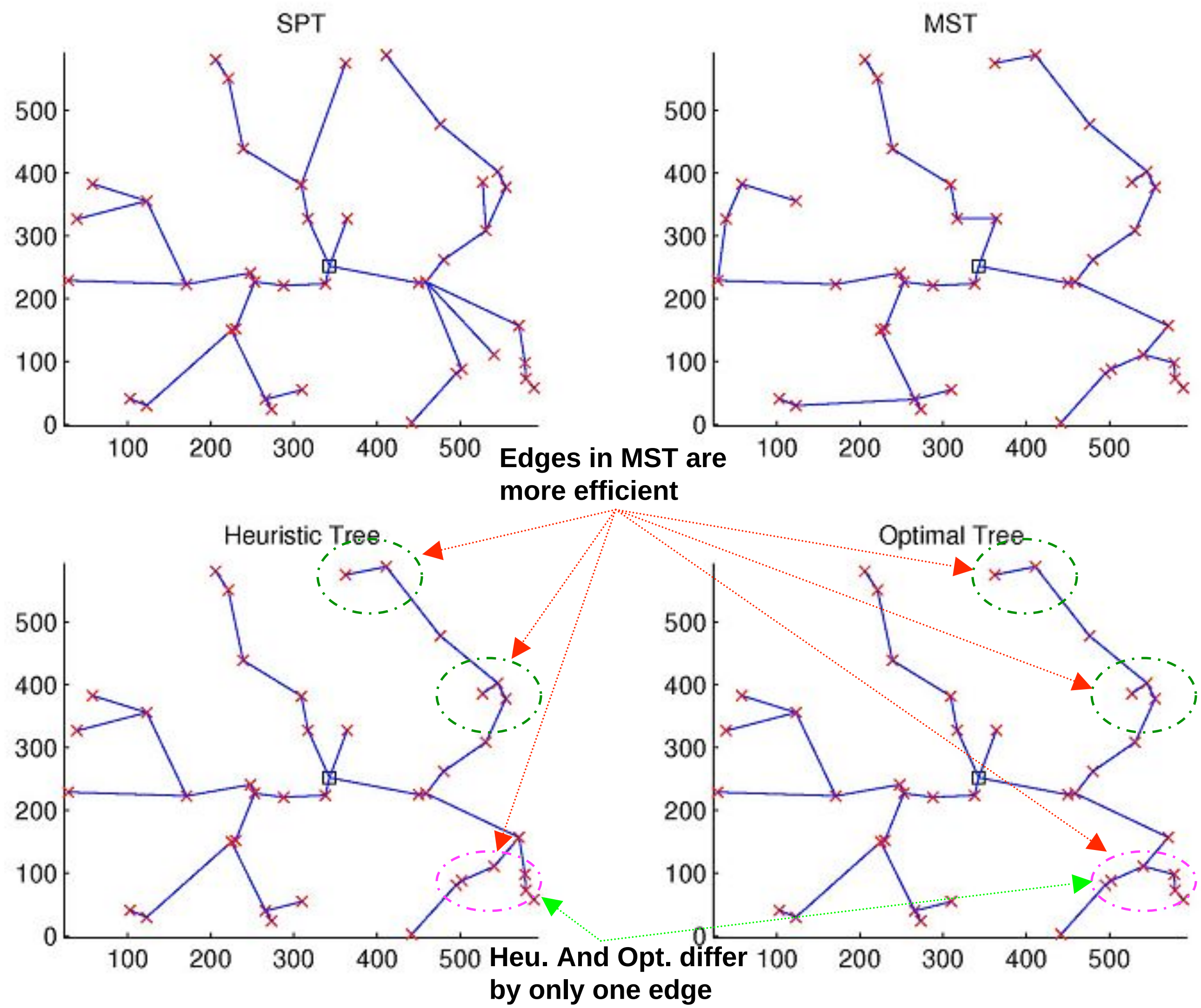
Two Main Methods:

- Search over all combinations of SPT and MST
- Start from an SPT, search from greatest depth nodes down to the sink
    - Exchange parent to that of parent in MST
    - If new tree is valid and cost is lower (for same distortion), change the parent from the SPT to that in the MST

[1]. G. Shen and A. Ortega, “Joint routing and 2D transform optimization for irregular sensor network grids using wavelet lifting”, IPSN’08.

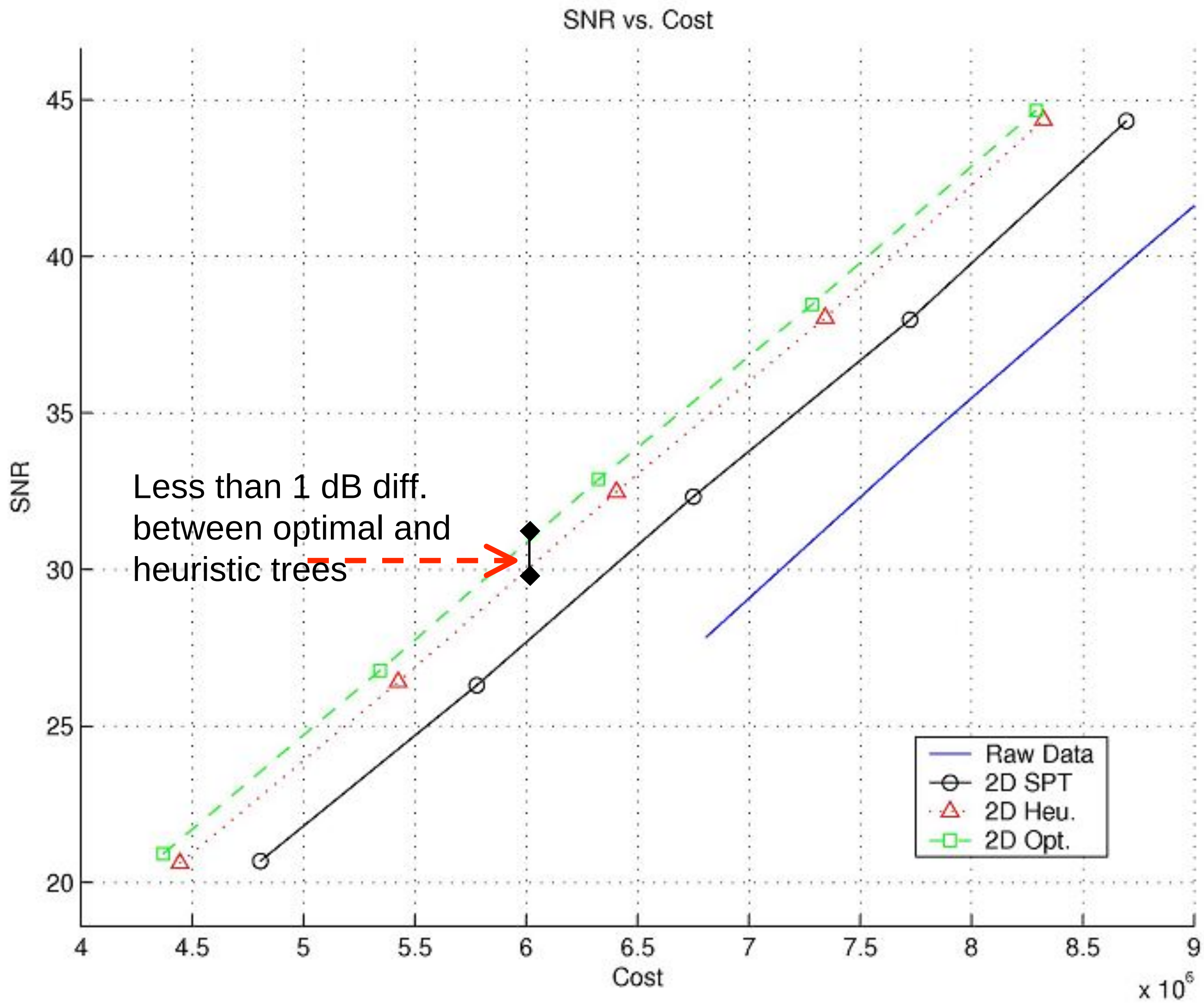
Joint 2D Transform and Routing Optimization

Results for Uniform Network



Joint 2D Transform and Routing Optimization

Results for Uniform Network (Continued)



Broadcast Nodes - Overview

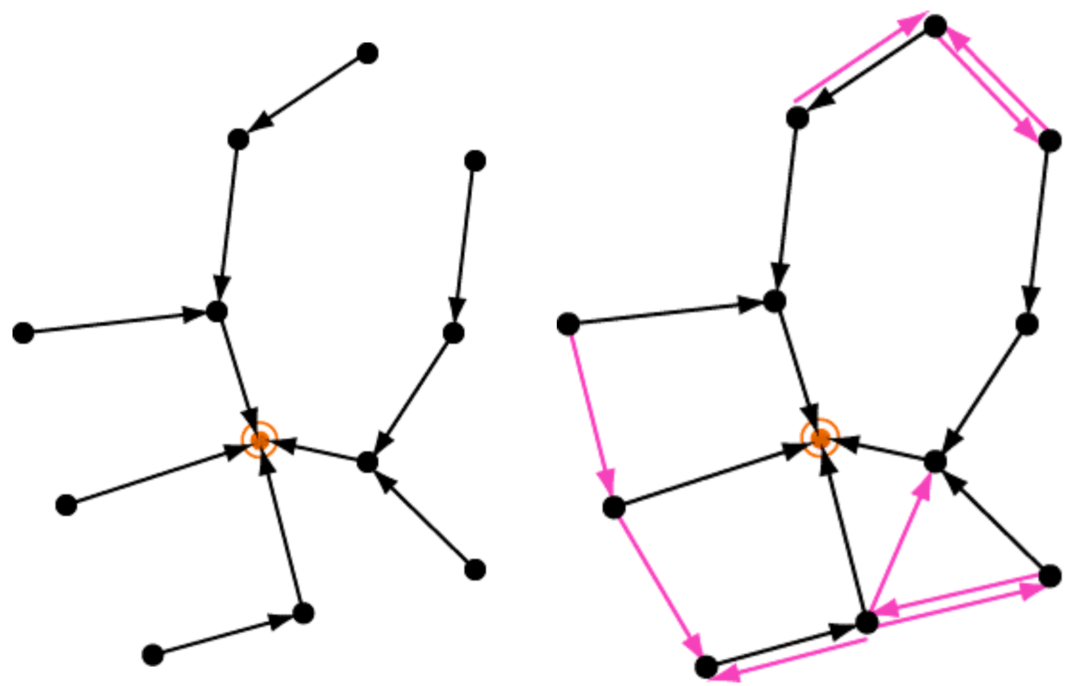
Node communications are not directional; multiple nodes may be able to receive a single transmission

Goal:

- Design a communication strategy to exploit these extra communications

Motivation:

- Broadcast come for free
- The cost of the acquiring messages at additional nodes is negligible in many realistic scenarios



Tree-structure communication paths to the sink node

Same network with possible additional "free" communications arising from the broadcast nature of the links

Exploiting Broadcast Capability (G. Shen, S. Pattem, A. Ortega – USC)

Goal:

- Utilize broadcast to enhance performance of our current system

Motivation:

- Broadcast allows nodes to transmit data to multiple neighbors (more than their neighbors defined in a routing tree)
- Can use this to further de-correlate data

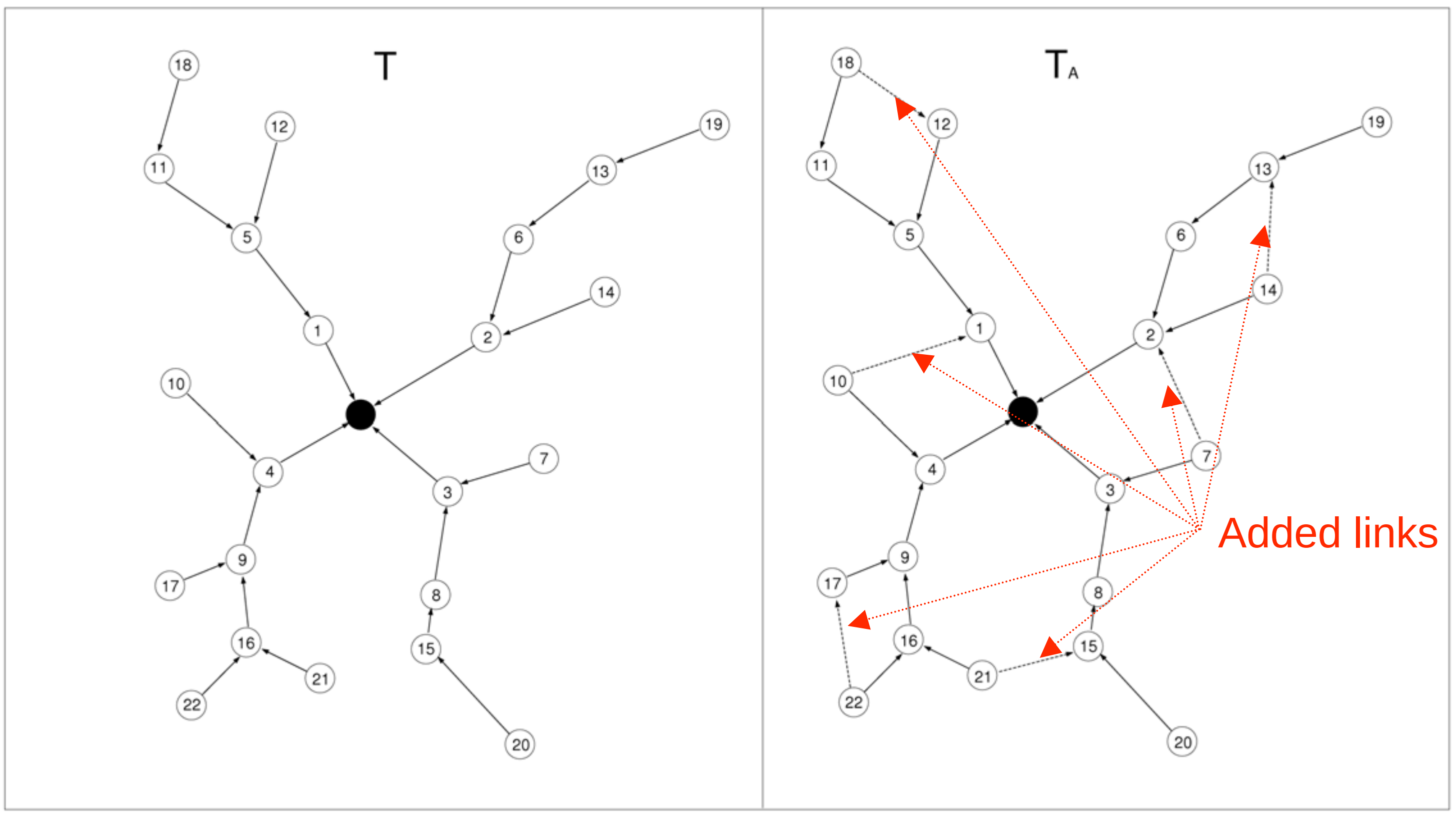
Our Proposed Method:

- Start with an initial routing tree T
- Exploit broadcast whenever possible along the tree
    - Augment the initial tree T to include broadcasts
    - Can even use more general graphs, forward data along T

Exploiting Broadcast Capability

Preliminary Broadcast Technique

- While forwarding along T, even node broadcasts at depth d can reach multiple odd nodes at depth d+1, d+3, … , d-1, d-3, …
- Exploit these broadcasts by augmenting T into the graph T_A (see figure)
- Compute **predicts along T_A** and **updates along T**



Exploiting Broadcast Capability

Comparisons of Predict Computations

- Having *more neighbors* can produce *lower predict energy*
- *Lower energy predicts* require *fewer bits* to encode

Predict equations along T

$$
\begin{aligned}
d_{1,T} &= x_1 - x_5 \\
d_{2,T} &= x_2 - (x_6 + x_{14})/2 \\
d_{12,T} &= x_{12} - x_5 \\
d_{13,T} &= x_{13} - (x_6 + x_{19})/2 \\
d_{15,T} &= x_{15} - (x_8 + x_{20})/2 \\
d_{17,T} &= x_{17} - x_9
\end{aligned}
$$

Predict equations along T_A

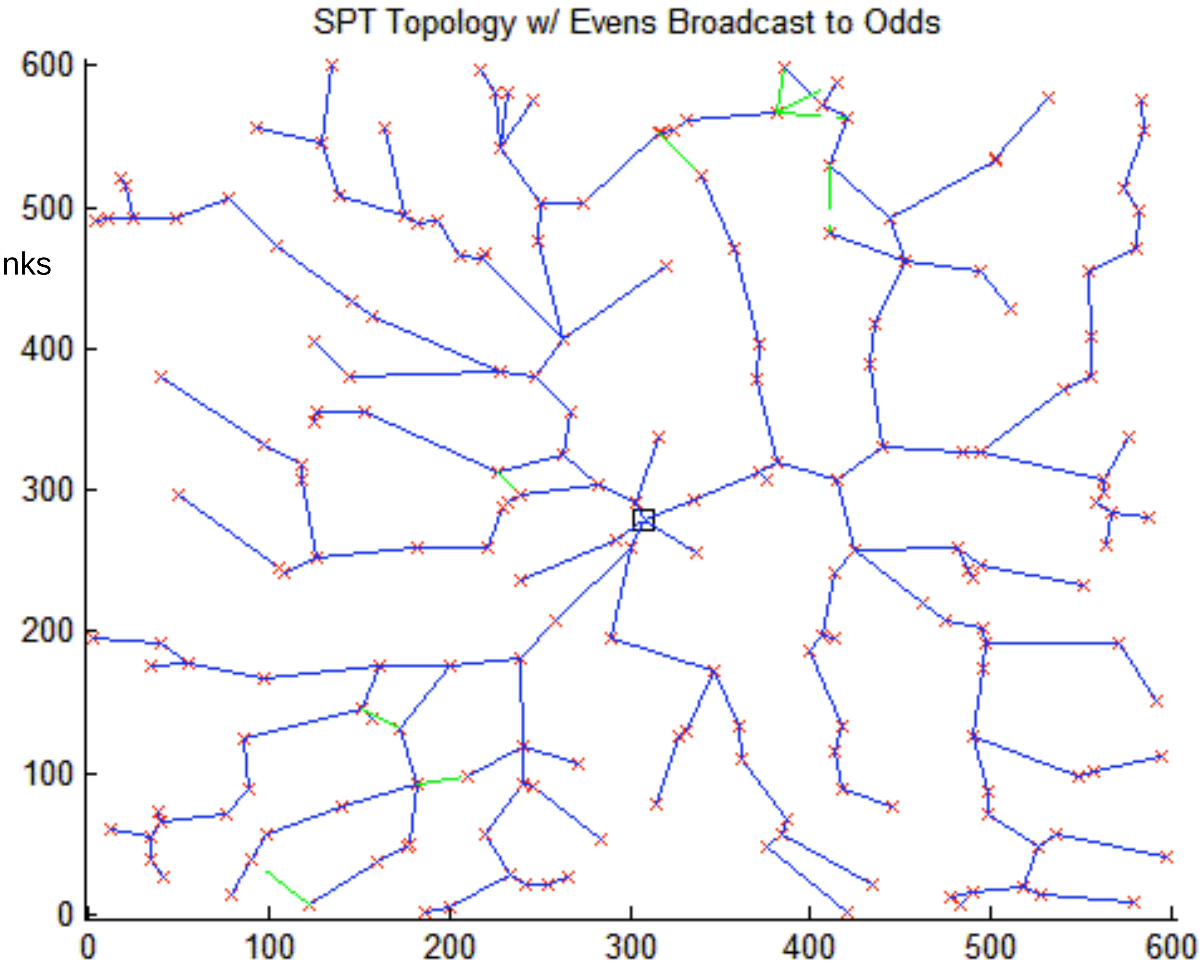
$$
\begin{aligned}
d_{1,T_A} &= x_1 - (x_5 + x_{10})/2 \\
d_{2,T_A} &= x_2 - (x_6 + x_{14} + x_7)/3 \\
d_{12,T_A} &= x_{12} - (x_5 + x_{18})/2 \\
d_{13,T_A} &= x_{13} - (x_6 + x_{19} + x_{14})/3 \\
d_{15,T_A} &= x_{15} - (x_8 + x_{20} + x_{21})/3 \\
d_{17,T_A} &= x_{17} - (x_9 + x_{22})/2
\end{aligned}
$$

Exploiting Broadcast Capability

Preliminary Results

- Uniform 200 node network with highly correlated AR-2 data

Green – broadcast links
Blue – tree links



Exploiting Broadcast Capability

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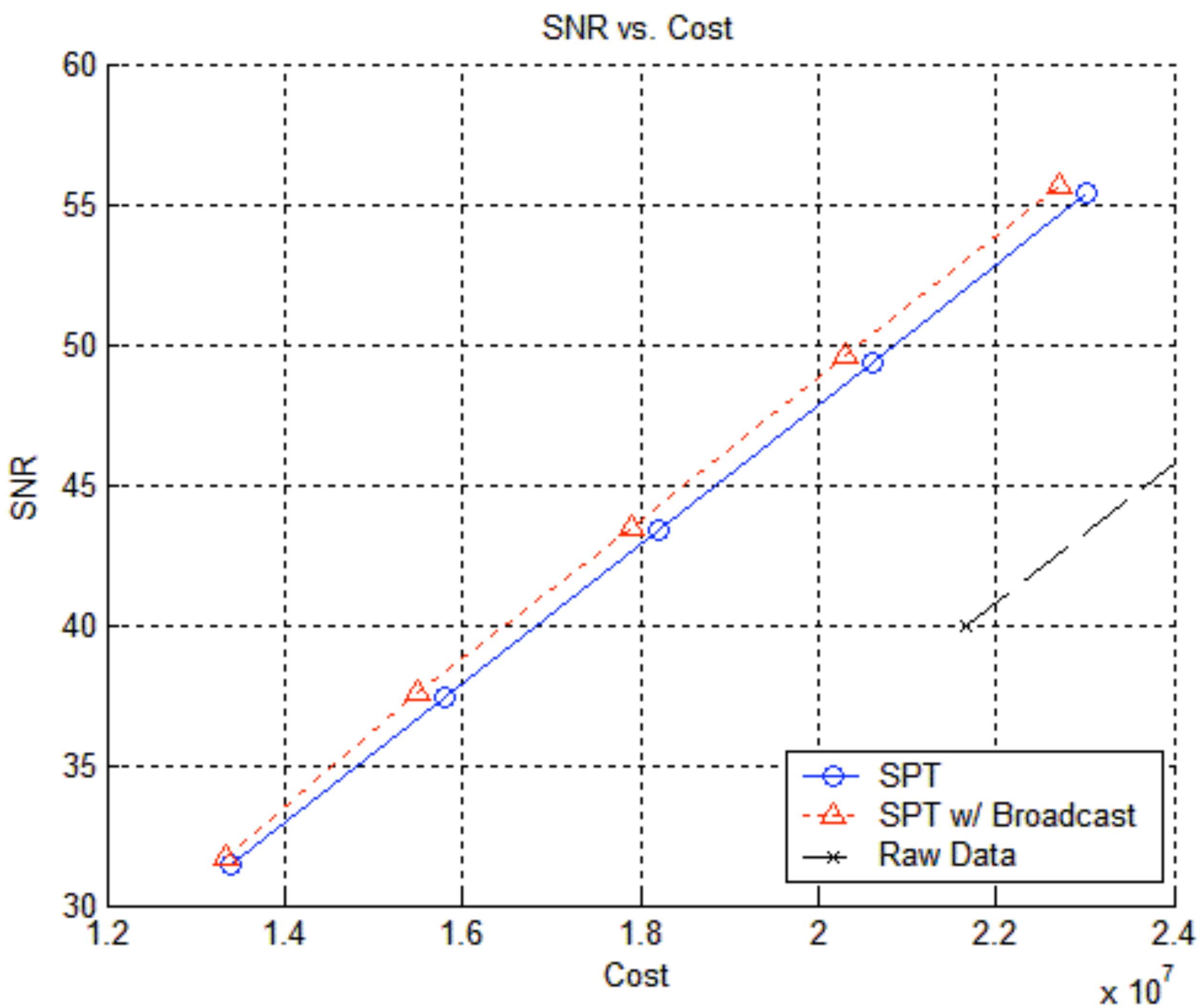
Preliminary Results (Continued)



JPL

Erasure Correcting Codes - Link Quality Considerations (M. Cheng, S. Dolinar - JPL)

Goal: Study and implement various erasure-correcting codes for sensor networks that achieve more reliable sensor-to-sensor communications

- Reduces number of retransmissions, resulting in energy savings
- Allows for more robust system performance under varying degrees of link quality

Motivation: Data transmissions between nodes are subject to erasures with probability p_ε, resulting in costly retransmissions that increase overall energy consumption

Current Results:

- Developed software to generate and to simulate performance of:
  - State-of-the-art LT rateless codes
  - Blake's new windowed erasure-correcting codes
- Selected LT codes for implementation based on lower complexity and greater maturity (but not yet implemented)

Mote Implementation
(S. Pattem, B. Krishnamachari – USC)

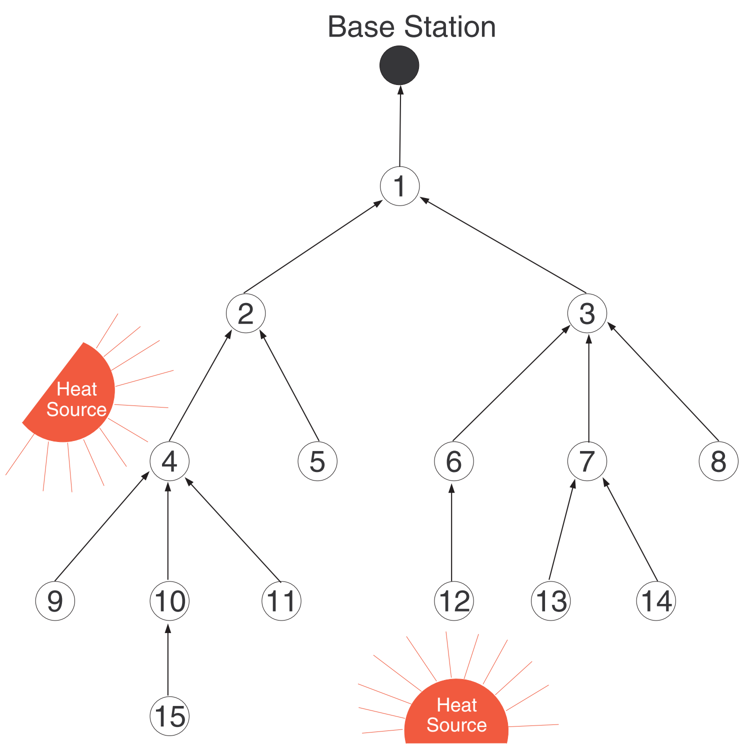
Implementation Related Goals:

- Provide in-lab testbed for algorithm performance evaluation
- Identify and establish a real environment for real time algorithm implementation

Current Results:

- Hardware implementation of invertible 2D wavelet
  - Tmote Sky devices (CC2420 radio)
- Storage and packetization
- Distributed and flexible operation (any given tree)

Mote Implementation

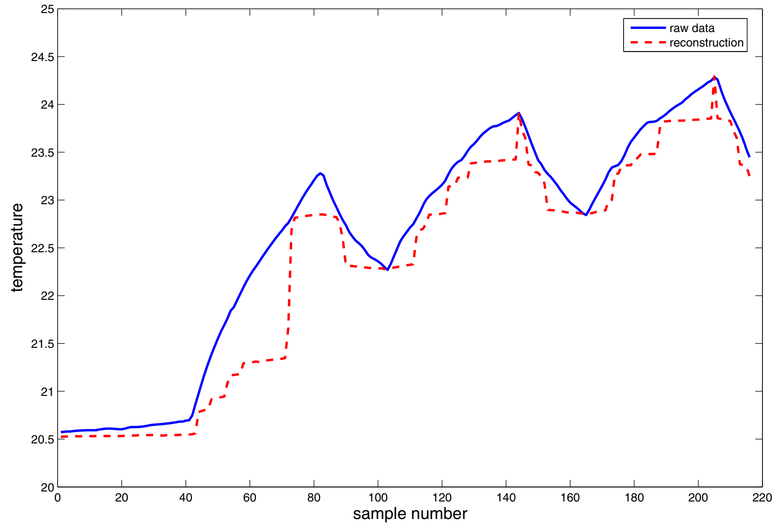


Experimental setup

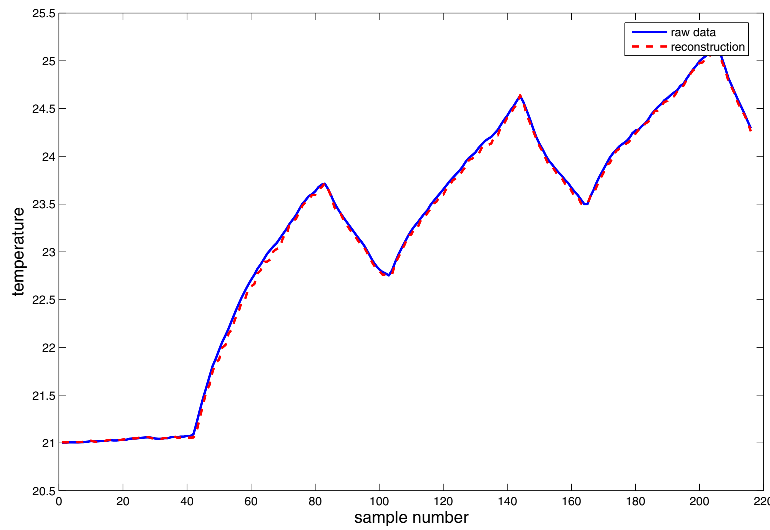
Measurements are 16 bits

bits per sample	normalized cost	average MSE
2	.79	.036
4	.85	.00057

Result summary



node 12, 2 bits



node 12, 4 bits

Mote Implementation

Results Show:

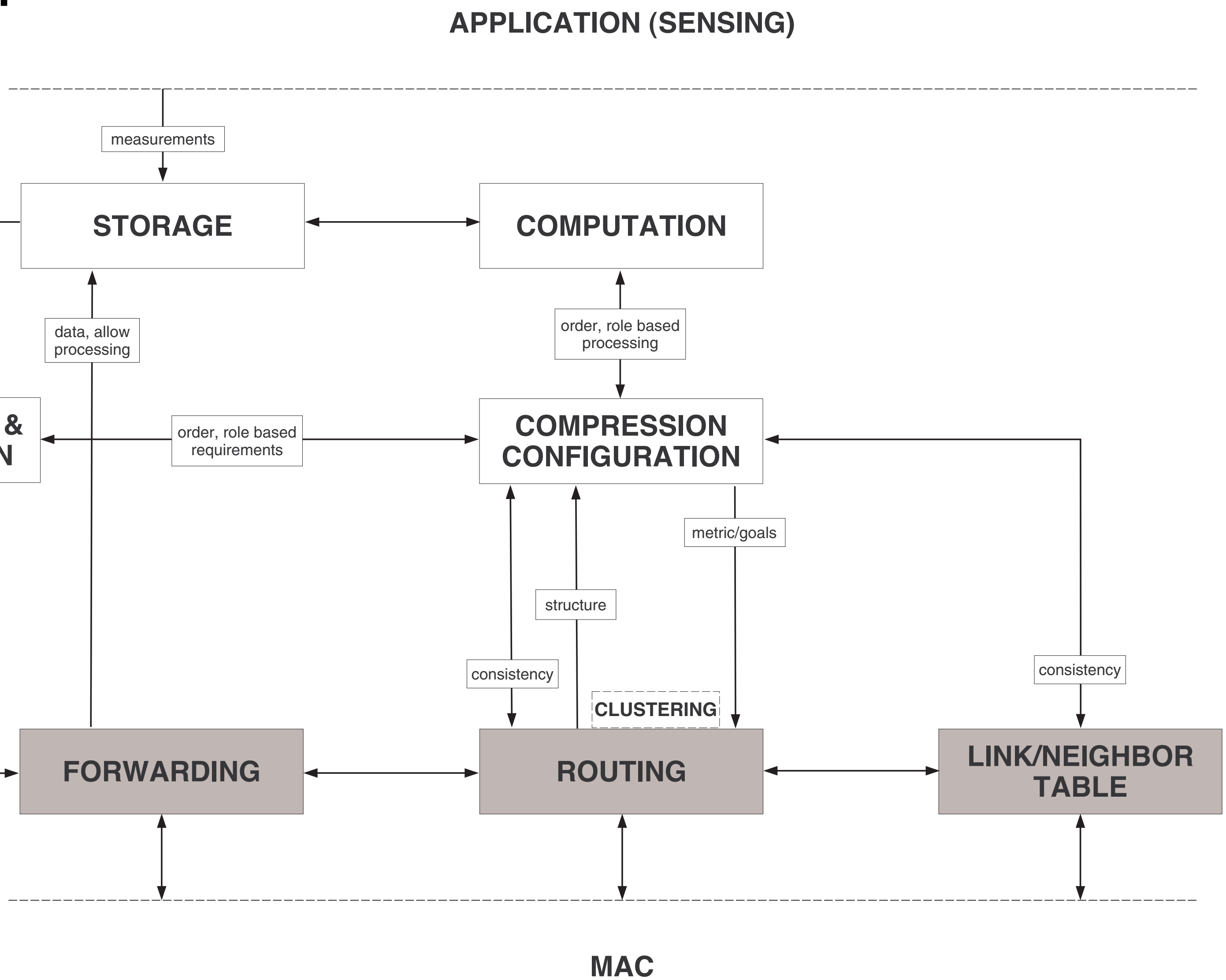
- Correctness of 2D wavelet implementation
- Tradeoff between cost and reconstruction quality

Looking Ahead

- For wide usage, need an architectural view that defines:
  - Where compression fits into standard network stack
  - Interactions between compression and networking components
  - Modules in compression component
  - Robustness mechanisms for distributed compression

Mote Implementation

Our Proposed Architecture



Future Work

- **Data Compression Methods**
  - Extensions of tree based 2D wavelets (i.e., “Tree-lets”)
  - Filter optimization methods
  - Extend temporal coding methods to tree based 2D wavelets

- **Networking and Routing Methods**
  - Node selection
  - Network initialization
  - Link quality robustness
  - Automatic reconfigurability

- **Real Mote Implementation**
  - Integrate entropy coding and erasure correcting codes
  - Develop software that handles an arbitrary sensor web topology
  - Test our algorithms in an outdoor realistic environment

Questions

???