Combined Source-Channel Decoding and Transmission Censoring for Power Reduction in a Wireless Sensor Network

by

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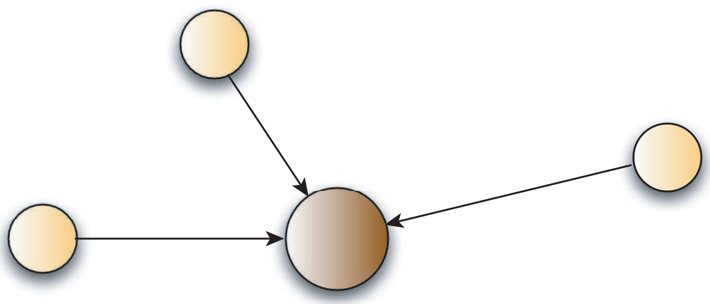
Wireless Sensor Networks

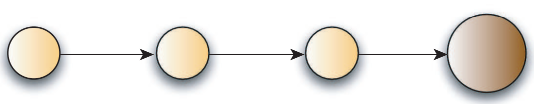
- Small battery-powered sensors
- **Energy efficiency** critical → extend battery lifetime
  → minimize replacement
- Environmental sensors: remote or fragile locations
- Poor link quality → retransmissions
- Error-correction coding (**ECC**) reduces energy:
  1. Fewer retransmissions
  2. Lower transmit power for same BER
- costs of ECC: encoding/decoding complexity, lower rate
  - use simple codes, encoding only at sensor nodes

Network Models



Star Network

- Several **sensor nodes**:
  Limited computational/energetic resources
  - send quantized msmt to gateway node
- One **gateway or processing node**:
  Large computational/energetic resources
  Decoding occurs here
- **Binary Symmetric Channel:**
  bit-flipping channel
  adds noise $n \in (0, 1)$ to transmitted bits
  BSC good model for radio rcvr output



Relay Network

- Nodes forward incoming msgs
  + encode/xmit own msgs
- Nodes could do minimal decoding

Environmental Sensing Network: Redwood Forest

NAU WiSARDNet Lab, Humboldt State U and Duke U Clark Lab

- **Measuring:** temperature, light, humidity, soil moisture
- **Highly correlated** measurements:
  - same parameter, tree to tree, same time
  - same parameter, same tree, over time; cross-correlation $r_{ij} > 0.9,\ i \neq j$
  - different parameters, same tree, same time

Correlated Sources (Measurements)

Can we incorporate **model of source correlation** into decoder to improve performance?

- **Assumption: Know source model**
  - Initial training period gathering data for source model
  - Develop covariance matrix Σ, mean μ for parameters
- **Source Model** could include:
  1. cross-node correlation of same parameter at fixed time
  2. same-node correlation of same parameter over time
  3. same-node correlation of different parameters at fixed time
- Source model changes over time
  - Diurnal
  - Seasonal
  - Adaptive model or updated from gateway

Source Model for Cross-Node Correlation

Definitions:

- Sensor node i measures m_i; N sensor nodes.
- Gaussian-distributed $m \sim \mathcal{N}(\mu_m, \sigma_m^2)$
  All sensor nodes have **same mean, variance**
- Quantized measurement $u_i = Q(m_i)$
- Encode $u_i \longrightarrow$ cw v_i
- $V =$ **Product cw** of all N sensors;
- $V_{\imath} =$ product cw with cw i removed
- $M =$ vector of all N measurements
- $N =$ binary noise vector
- $R = V + N =$ received noisy product cw

Iterative Source-Channel Decoding (ISCD)

- **Iterative** source-channel decoding (ISCD) proposed by Görtz, ISIT 2000
- ISCD for source and channel coding, Bauer and Hagenauer DCC 2001
  - **source coding**: variable-length code (VLC)
  - **channel coding:** convolutional code
- ISCD for correlated source: Hagenauer and Görtz, ITW 2003
  - **source**: first-order Markov source
  - **channel coding:** rate 1/2 convolutional code

Source Model

Source model stored at gateway node/decoder:

- $p(V)$ or $p(M)$: *a priori* on product codeword V, quantized msmt M
- $p(R|V)$ for MAP SC decoder ... OR ...
- For iterative SC decoder:
  - **conditional symbol probs** $p(v_i|V_{/i})$ or $p(m_i|M_{/i})$ for cw i based on other cws; $V_{/i}$ is vector of all other cws v_j, $j \neq i$

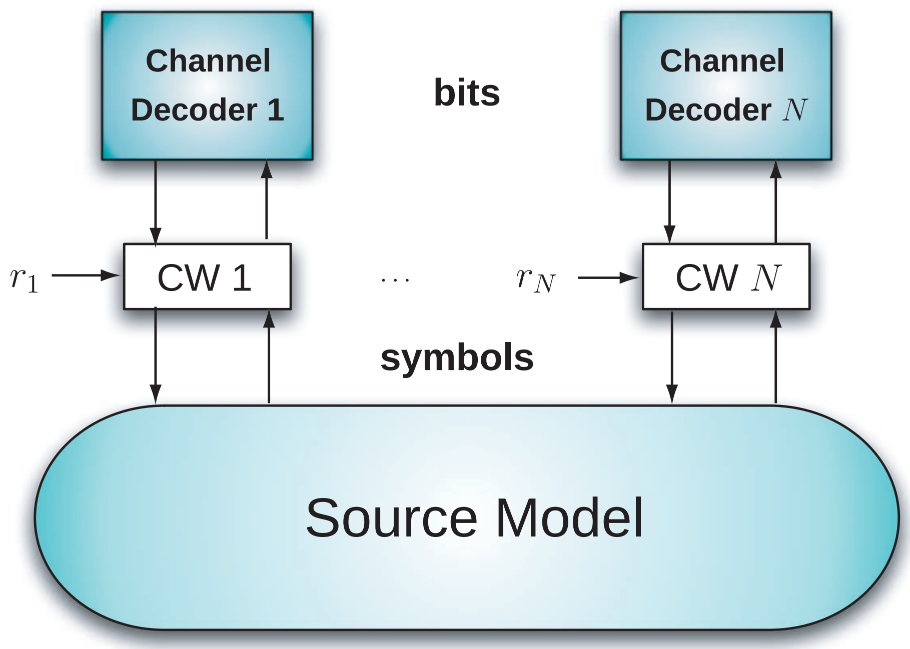
Simplifying assumptions for model:

- $p(v_i|V_{/i})$ same for all i (independent of sensor node)
- May not be true, but simplifies model; could be calculated for all nodes
- Similarly, in deriving source model: correlation r_{ij} assumed constant for all $i \neq j$

Combined Channel/Source Model Decoder I

- Combine **Channel Decoding** and **Probabilistic Source Model**

Soft-Decision Iterative Decoder:



- Separate **channel decoders** and **source model decoder**
- Source model contains **conditional symbol probs** or **bitwise conditional probs**
- **Iterate:** send probs btw channel decoders $\Leftrightarrow$ source model decoder

Source Model Decoder for Iterative SC Decoding

Incorporate correlation

Include other cws $V_{/i}$ (all except cw i):

$$\hat{v}_i = \arg\max_{v_i} p(v_i) = \arg\max_{v_i} \underbrace{\sum_{V_{/i}} p(v_i|V_{/i})p(V_{/i})}_{\text{marginalization}}$$

- Use with ISCD: $p(v_j) = \prod_{k=1}^{n} p(v_{j,k})$ from channel decoders

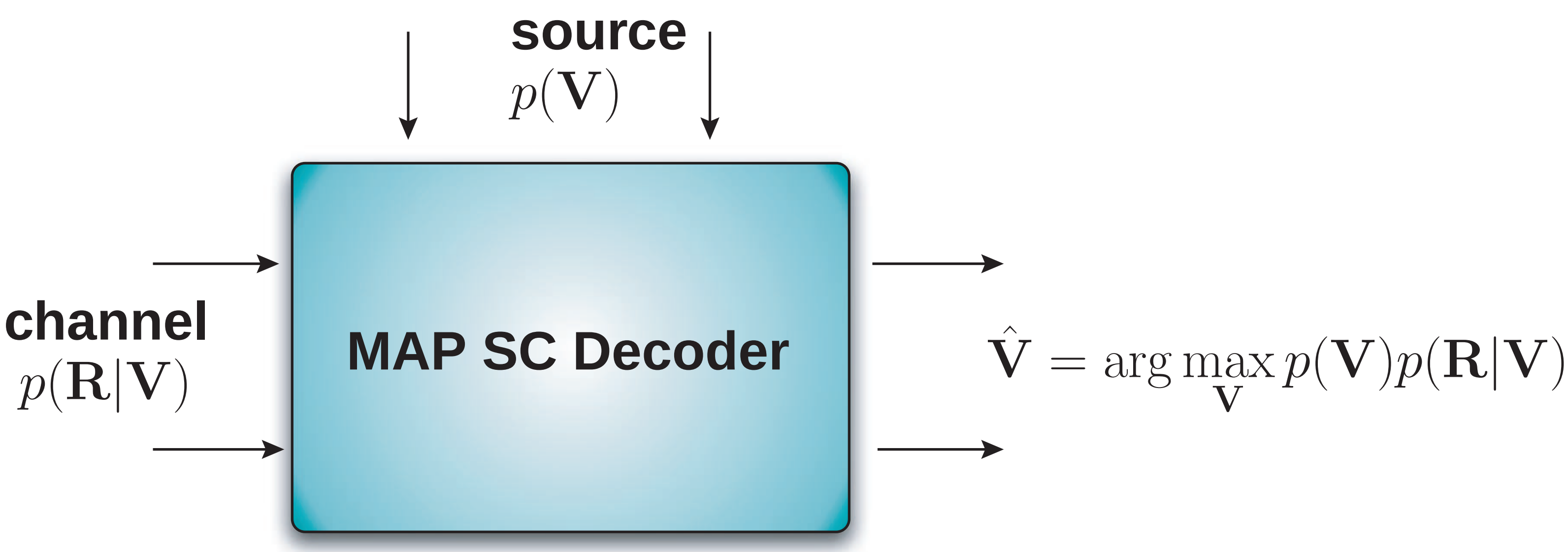
$$p(V_{/i}) = \prod_{j \neq i} p(v_j)$$

Reduce complexity:

- Only store largest $p(V_{/i}) > 1e-07$

Combined Channel/Source Model Decoder II:

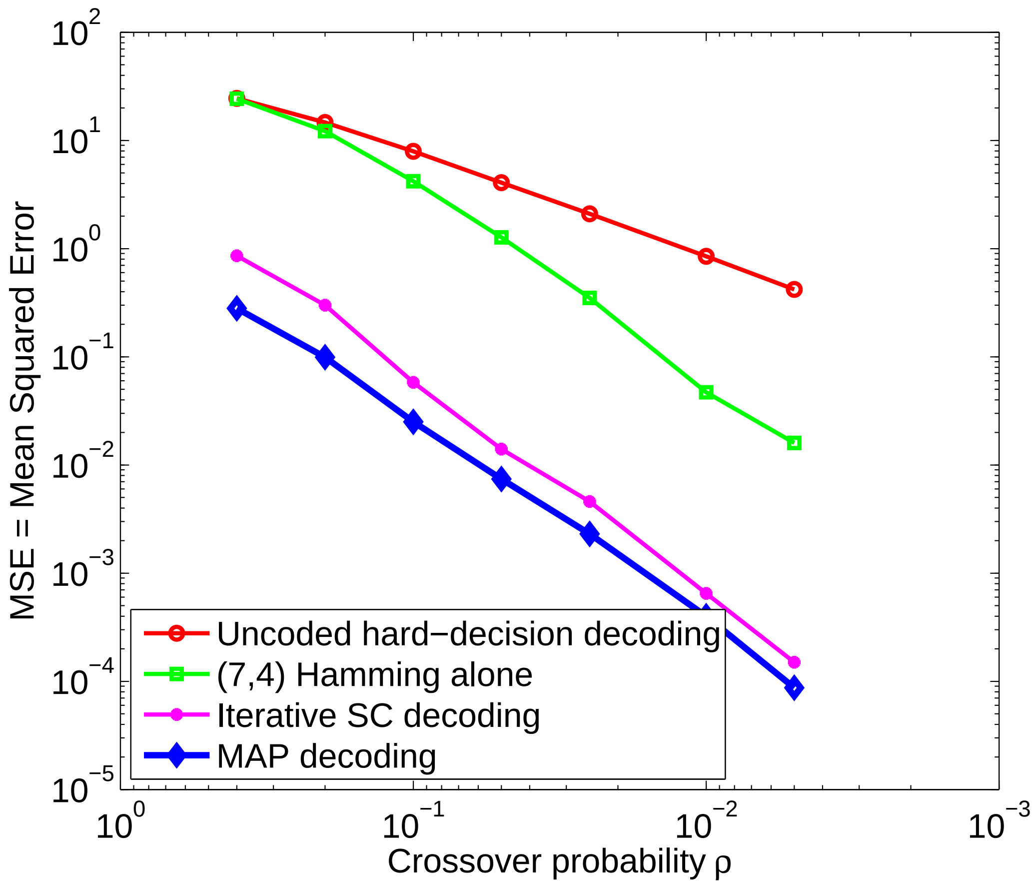
MAP (maximum *a posteriori*) Decoder:



- **Source-Channel MAP decoder** practical for
  - Small network: small N, short code, small size V
  - Highly-correlated network
- **Iterative source-channel decoder** more practical as size V increases
- MAP decoder provides performance benchmark

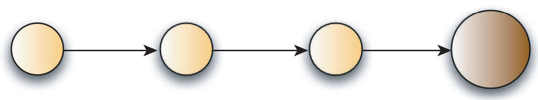
Iterative Decoding: (7,4) Hamming/Source Decoder

Star Network, 3 sensors, BSC: Crossover Probability ρ vs MSE



- $\sigma_m^2 = 0.2$, Correlation $r = 0.9$
- **Channel code:** (7,4) Hamming
  Channel decoder:
  BCJR APP SISO on PC trellis
- **Source Decoder**:
  conditional **symbol** probs
  $p(v_i = A | V_{/i} = Q)$
- **Iterative decoder:** 5 iterations
- **MAP decoder** uses priors
  on product codeword $\mathbf{V}$
  $\hat{\mathbf{V}} = \arg\max_{\mathbf{V}\in\mathcal{V}} p(\mathbf{R}|\mathbf{V})p(\mathbf{V})$

Relay Network



Relay Network

- Nodes forward incoming msgs
  + encode/xmit own msgs

Transmission Censoring:

- Each sensor node decides:
  Censor some, none or **all** of its messages?
- How can a message be recovered if not sent?
  Decoder fills in missing messages based on:
  1. Codeword space C (channel decoder)
  2. Source model (source decoder)
- Some **performance loss** expected
- **Energy reduction** from censoring messages
- Some **energy expenditure** from censoring algorithm

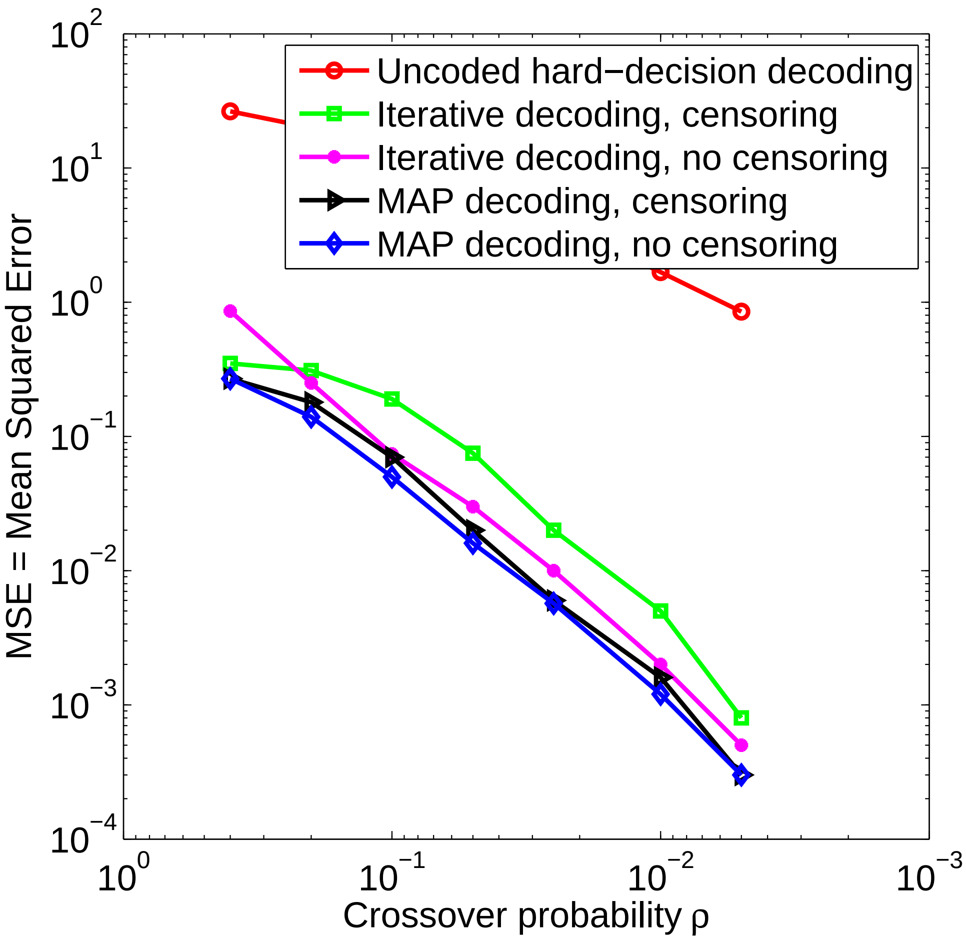
Transmission Censoring Decision

How does sensor node decide when to **censor a message**?
Or, which of several messages should it censor?

- Can next node recover missing message(s)?
- Sensor node **emulates decoding** at next node
- Must have channel knowledge (ρ) to emulate rcvd msg at next node
- Sensor node uses iterative decoder w/source model for partial V
- Output of decoder = $\hat{V}_{\text{censor}}$
- $\hat{V}_{\text{censor}} = V$? Did decoder recover missing msg(s)?
  Or: **tolerate some errors** - is decision within threshold?
- If so, censor them!
- If not, censor fewer msgs, or no censoring
- Several possible censoring options

Relay Network with Censoring: Source-Channel Decoder

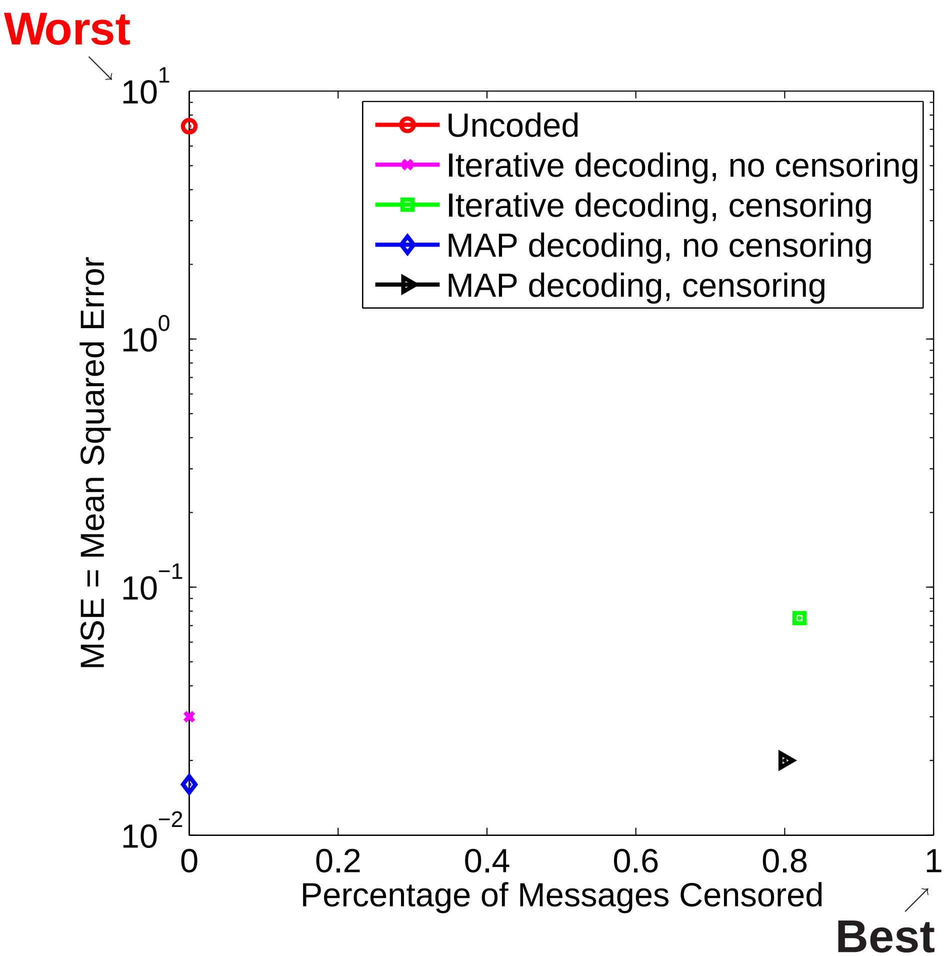
Relay Network, 3 sensors, BSC: Crossover Probability ρ vs MSE



- $\sigma_m^2 = 0.2$, Correlation $r = 0.9$
- 2 msmt/sensor $\rightarrow$ 6 total msmts
- **Channel code:** (7,4) Hamming
- **Source Decoder**: conditional symbol probs $p(v_i = A|V_{/i} = Q)$
- **Iterative Decoder:** 5 iterations
- Small performance loss with:
  - transmission censoring vs no censoring
  - iterative decoding vs MAP decoding

Transmission Censoring Percentage

Relay Network, 3 sensors, BSC: Percentage of Messages Censored vs MSE



- **Transmission censoring**
  At each sensor node:
  Node censors only its own msgs
  Censor **some**, **none** or **all** of msgs?
- BSC $\rho = 0.05$; Correlation $r = 0.9$
- Tradeoff: **energy** and **performance**
- Highly correlated environment:
  Minimal performance loss
  with censoring
- Save energy by not xmitting msgs
  Censoring policy costs energy
  $E_{\text{xmit}} > E_{\text{censor}}$?

Source Model Complexity

Source model complexity increases with

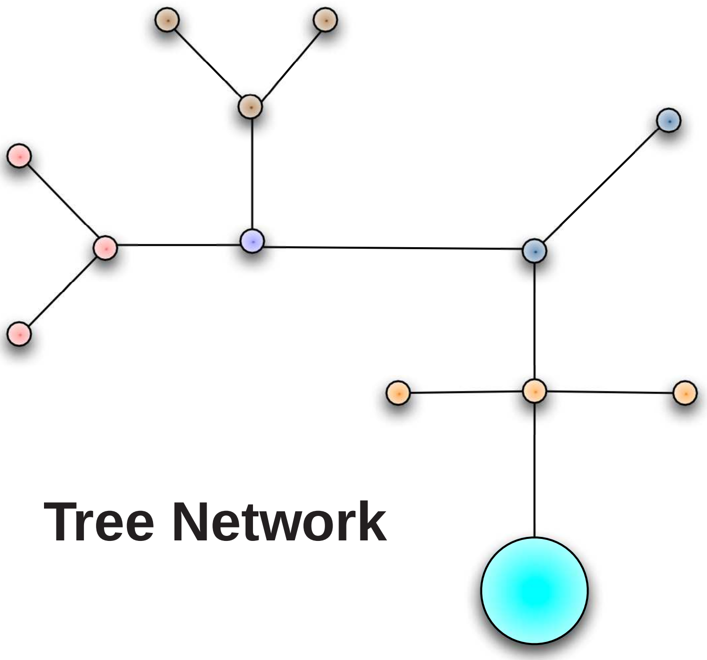
- More sensor nodes
- More msmts taken per node
- Greater msmt bit precision $\rightarrow$ larger cw alphabet
- Less correlation btw sensor nodes
- Inclusion of less probable cws
- Multi-variable correlation

Reducing Source Model Complexity

Reduce complexity by

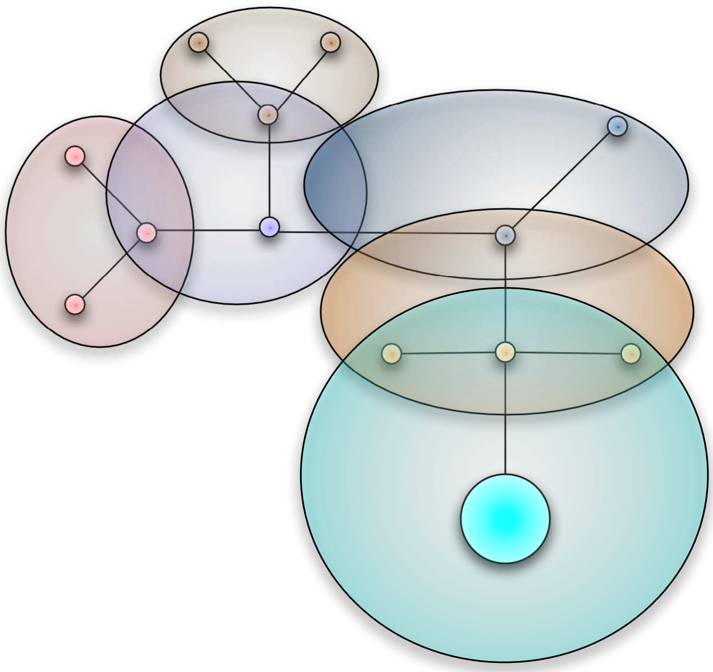
- Using local source models at sensor nodes
- Reducing precision in source model:
  source model covers subset of data bits;
  lowest correlation btw LSB
- Only use source model in high correlation
- Transmit low-probability data w/stronger code
  No source decoding

Tree Network



- Combination of star and relay network
- Model typical of actual network topology
- Ex: 12 sensor nodes, 1 processing node
- Source model becomes v large unless high correlation btw all nodes

Tree Network: Local Source Models



6 Local Source Models

- Reduce complexity:
  Use local source models
- Source models limited to highly correlated nodes
- Ex: Each source model covers 3-4 nodes
- Overlapping source models

Conclusions

- Combining channel coding and **highly-correlated** source model at decoder: **large improvement in MSE** $\rightarrow$ reduced network power consumption
- MAP SC decoding feasible in highly correlated environment
  - small subset of product CWs V probable
- ISCD has MSE performance close to MAP SCD
- **Transmission censoring** at sensor nodes:
  large reduction in msgs sent with **small performance loss**
  in **highly-correlated** network
- Proof of concept: small codes, small network
- Work in progress:
  - Use data from existing network
  - Implement ISCD in existing network
  - Match codes to source model