Collaborative Processing in Resource-constrained Distributed Environments

Hairong Qi, Associate Professor
Electrical Engineering and Computer Science
University of Tennessee, Knoxville
http://www.eecs.utk.edu/faculty/qi
Email: hqi@utk.edu
AICIP Research

• Advanced Imaging and Collaborative Information Processing (AICIP)
• Collaborative processing
  – Scalar sensor network
  – Visual sensor network
  – DARPA, NSF, ONR

• Advanced Imaging
  – Automatic target recognition and subpixel recognition using multi-hyper-spectral imaging
  – Medical imaging using infrared
  – US Army, ONR
AICIP Research (Cont’)

• Graduated 7 Ph.D. students and 16 M.S. students with thesis option
• Currently advising 7 Ph.D. students and 2 M.S. students
• Four sensor network testbeds
  – Motes, sensoria nodes, MSP, and spoonbot nodes
• Webpages
  – http://aicip.ece.utk.edu
  – http://panda.ece.utk.edu/wiki
Internet vs. Sensornet

To be able to understand, monitor, and interact with the physical world (real world) in a timely, intelligent, and reliable fashion.

- Low cost
- Small size
- Power constraint
- Computational limited
- Bandwidth limited
- Certain degree of intelligence
Application-Oriented Design

Traditional TCP/IP Protocol Stack

Sensor Network Protocol Stack
Sensor Network Protocol Stack

- Application-oriented
  - Task-adaptive
  - Mission-oriented
- Energy-efficient

Two Contradictory Requirements

- **Energy-efficiency**
  - Operating system
  - Communication
  - Routing
  - Computing
  - etc.

- **Fault-tolerance**
  - Robust response
  - Compensation

**Collaborative Processing concerns**
- Lower-power communication or computation
- Space-time processing
- Distributed and fault-tolerant algorithms
- Adaptive systems
- Decision theory

**Eliminate redundancy**

**Need redundancy**
Research Focus

• Develop energy-efficient collaborative processing algorithms with fault tolerance in sensor networks
  – Where to perform collaboration?
    – Computing paradigms
  – Who should participate in the collaboration?
    – Reactive clustering protocols
    – Sensor selection protocols
  – How to conduct collaboration?
    – In-network processing
    – Self deployment
Challenges in SCNs (Smart Camera Networks)

• The coverage problem
  – Directional sensing vs. Omni-directional sensing
  – Occlusion vs. no occlusion

• The clustering problem
  – Geographical neighbor vs. Semantic neighbor
  – Reactive clustering

• The data aggregation problem
  – What to propagate? (application oriented)
  – Distributed protocol?

• The application development
  – Target detection and localization
  – Target tracking
Challenge 1: MTD (Multiple Target Detection)

- Single target detection
  - Energy threshold
  - Energy decay model: \( E_{\text{obs}} = \frac{E_{\text{source}}}{d^\alpha} \)

- Multiple target detection
  - Why is multiple target detection necessary?
  - Requirements: energy-efficient & bandwidth efficient
  - Multiple target detection vs. source number estimation

Assumption: 
\[ \text{size}(S) = \text{size}_t \]

Target separation

\[ S = WX \]

\( S \) source matrix
\( X \) observation matrix
\( W \) unmixing matrix

Speaker separation
Source Number Estimation (SNE)

\[ \hat{m} = \arg \max_m P(H_m \mid X) \]

\[ L(m) = \log p(x^{(t)} \mid H_m) \]

\[ = \log \pi(\hat{\alpha}(t)) + \frac{1}{2} (n - m) \log(\frac{\hat{\beta}}{2\pi}) - \frac{1}{2} \log |A^T A| - \frac{\hat{\beta}}{2} (x(t) - A \hat{\alpha}(t))^2 \]

\[ - \left( \frac{mn}{2} \log(\frac{\hat{\beta}}{2\pi}) + \frac{n}{2} \left( \sum_{j=1}^{m} \log \hat{a}_j \right) + mn \log \gamma \right) \]

Estimation accuracy is progressively improved

\[ I_i \text{ includes} \]

\[ [A]_i \]

\[ [a^{(t)}]_i \]

\[ \varepsilon_i \]

\[ [\text{Term1}]_i \]

\[ [\text{Term2}]_i \]

\[ \ldots \]

\[ [\text{Term7}]_i \]

Transmitted informat

Progressive Update of log-likelihood function:

\[ L_i(m) = L_{i-1}(m) + f(x_i^{(t)}) \]

\[
L(m) = \log \pi(\hat{a}(t)) + \frac{1}{2} (n - m) \log \left( \frac{\hat{\beta}}{2\pi} \right) - \frac{1}{2} \log |A^T A| - \frac{\hat{\beta}}{2} (x(t) - A \hat{a}(t))^2
\]

\[-\left[ \frac{mn}{2} \log \left( \frac{\hat{\beta}}{2\pi} \right) + \frac{n}{2} (\sum_{j=1}^{m} \log a_j) + mn \log \gamma \right] \]

\[
[Term1]_i = [Term1]_{i-1} - \frac{1}{\alpha} \exp(-2\alpha [a_k]_{i-1}) \left[ \exp(-2\alpha w_{k,i} x_i^{(t)}) - 1 \right] - w_{k,i} x_i^{(t)}
\]

\[
[Term2]_i = \frac{i - m}{i - 1 - m} [Term2]_{i-1} + \frac{i - m}{2} \log \left( \frac{i - 1 - m}{i - m} \right) + \frac{i - m}{2} \cdot \frac{(x_i^{(t)} - \sum_{k=1}^{m} A_{i,k} \hat{a}_k)^2}{\epsilon_{i-1}}
\]

\[ [Term3]_i \] only depends on the updating rule of mixing matrix \( A \)

\[
[Term4]_i = \frac{i - 1 - m}{i - m} [Term4]_{i-1} + 2\epsilon_{i-1} (x_i^{(t)} - \sum_{k=1}^{m} A_{i,k} \hat{a}_k) + (x_i^{(t)} - \sum_{k=1}^{m} A_{i,k} \hat{a}_k)^4
\]
Progressive Update at Local Sensors

\[ L(m) = \log \pi(\hat{a}(t)) + \frac{1}{2} (n - m) \log(\frac{\beta}{2\pi}) - \frac{1}{2} \log \hat{A}^T \hat{A} - \frac{\beta}{2} (x(t) - \hat{A} \hat{a}(t))^2 \]

\[-[\frac{mn}{2} \log(\frac{\beta}{2\pi}) + \frac{n}{2} \left( \sum_{j=1}^{m} \log a_j \right) + mn \log \gamma] \]

\[[\text{Term5}]_i = \frac{i}{i-1} [\text{Term5}]_{i-1} + \frac{im}{2} \log(\frac{i-1-m}{i-m}) + \frac{im}{2} \cdot \frac{(x^{(t)}_i - \sum_{k=1}^{m} A_{i,k} \hat{a}_k^{(t)})^2}{\epsilon_{i-1}} \]

\[[\text{Term6}]_i = \frac{i}{i-1} [\text{Term6}]_{i-1} + \frac{i}{2} \sum_{k=1}^{m} \frac{(w_{k,i} x^{(t)}_i)^2 + 2w_{k,i} x^{(t)}_i \hat{a}_k^{(t)}}{([\hat{a}_k]_{i-1})^2} \]

\[[\text{Term7}]_i \text{ only depends on the updating rule of mixing matrix } \hat{A} \]

Progressive update of mixing matrix \( \hat{A} \): BFGS method (Quasi-Newton method)

Progressive update of error: \( \epsilon_i = \epsilon_{i-1} + (x^{(t)}_i - \sum_{k=1}^{m} A_{i,k} \hat{a}_k^{(t)})^2 \)
Challenge 2 - Unmixing

• Wide existence of mixed pixels
  – Remote sensing imagery
  – Medical imaging
  – Biological microscopy

• Approaches
  – Increase spatial resolution?
  – Utilize spectral information?

• Mixed pixel decomposition
  – Classification vs. Decomposition
  – A mixture is decomposed into a set of endmembers (EM) and their fractional abundances
  – With certain physical constraints

• Important parameter
  – Number of endmembers
Linear Mixing Model

- The measured spectrum is a **linear combination** of endmember spectra weighted by their area proportions.
- Two physical constraints: non-negative and sum-to-one.
- It is a **convex combination**.

\[
x_{l \times 1} = A_{l \times c} s_{c \times 1}, \quad s \geq 0, \quad 1^T s = 1
\]
GDME Formulation

- Optimization formulation
  - Minimize negative entropy

- Optimization method
  - Lagrange multiplier method

- Lagrange function
  - Non-negative constraint is not explicitly incorporated
  - Three unknowns, not independent

\[
\begin{align*}
\text{minimize: } & f_0(s) = \sum_{j=1}^{c} s_j \ln(s_j) \\
\text{subject to: } & h_0(s) = 1^T s - 1 = 0 \\
& h(s) = As - x = 0 \\
& s_j \geq 0, \ j = 1, \ldots, c
\end{align*}
\]

\[
\begin{align*}
\text{min: } L(s, \bar{e}, \lambda_0) &= \sum_{j=1}^{c} s_j \ln(s_j) + \bar{e}^T (As - x) + (\lambda_0 - 1) \left( \sum_{j=1}^{c} s_j - 1 \right)
\end{align*}
\]
Convex Geometry

• Convex set
  – A set of points are linear combinations of some other set of points (vertices)

• Connection between LMM and convex geometry
  – Each mixed pixel resides within a simplex in c-1 space
  – Vertices are endmembers

• Unmixing algorithms
  – Reconstruct simplex (without PPA)
  – Find extreme pixels from the scene (with PPA)
  – Sensitive to noise
  – Do not consider approximation error
Non-negative Matrix Factorization

• Given matrix Y, find two non-negative matrices, such that

\[ Y_{n \times m} = W_{n \times r} H_{r \times m}, \quad W \geq 0, \quad H \geq 0, \quad r < m, n \]

• Optimization problem

\[
\begin{align*}
\text{minimize} & \quad f(W, H) = \frac{1}{2} \|Y - WH\|^2 \\
\text{subject to} & \quad W \geq 0, \quad H \geq 0
\end{align*}
\]

• Geometrically, find a simplex containing the data
  – No constraint on the simplex

• Non-unique solution

\[ (WD)(D^{-1}H) = WH \text{ for any positive matrix } D, D^{-1} \]

• Need more constraints to confine solution space
MVC-NMF Formulation

• Problem formulation
  – First term is the approximation error
  – Second term is the volume constraint

\[
\begin{align*}
\text{minimize} & \quad f(A, S) = \frac{1}{2} \|X - AS\|_F^2 + \tilde{\xi}(A) \\
\text{subject to} & \quad A \succeq 0, S \succeq 0, 1^T S = 1^T
\end{align*}
\]

• Internal and external force interpretation
  – First term serves as external force which expands the simplex to enclose all data points
  – Second term is internal force which makes the simplex as compact as possible
Challenge 3: Visual Data Aggregation

• Centralized solution - highest-confidence first
  – 1. Raise alarms on the hulls with globally highest confidences
  – 2. Withdraw the cones of the hulls from the ground
  – 3. If the highest confidence is larger than H, go back to 1

• Distributed solution: The info of each cone is relayed by the nodes whose voronoi cells overlap the cone area
  – The relay is stopped when the info either reaches the node at the cone’s perimeter or is found compatible with a local detection
    – Parallel with local detection process
    – Exempt from synchronization requirements
    – Generic for aggregating visual info
Distributed Solution

- Each node
  - independently raise an alarm on a local hull once the confidence of the hull is larger than all other hulls sharing same cones with it.
  - notifies related nodes to withdraw these same cones.
  - if the highest confidence of local hulls are larger than threshold $H$, go back to 1.
Challenge 4: Self Deployment and Mosaicking

- Cone mosaic of human visual system
- Cone mosaic of fish

Design Criteria

• Spatial uniformity
  – The filter array of each band should sample the entire image as evenly as possible

• Spectral consistency
  – An MSFA sample should have the same number of neighbors of a certain spectral band in a certain neighborhood

• Spectral sensitivity
  – The probability of appearance matches the effectiveness of each band in recognizing targets
Binary Tree and Checkerboard

• Binary tree
  – Nodes at each level have the same probability
  – Two children combined to form their parent

• Checkerboard pattern
  – Uniform distribution
  – The same sampling rate
  – Symmetric vertically, horizontally, diagonally
Generation of a 5-band MSFA

Step 1

Step 2

Decomposition

Subsam

Step 3