Collaborative Signal and Information Processing (CSIP)

Lecture 18

EE 493/593

Wireless Sensor Networks

Wireless Distributed Sensor Networks

- Communications
- Computing
- Signal Processing
- Internet Algorithms, Social Computing
- Computer Networks
- Operations research
- Physical, Biological, Social Sciences

CC:
- Game theory, auctions, incentives, pricing, cooperation
- Network algorithms
- Scale, complexity, interactivity
- Network design, Reliability
- Security, privacy, intrusion detection
- Massive data sets
- Geometry and visualization of networks

CSP:
- Signal processing for wireless comm
- Multimedia signal processing
- Collaborative/distributive signal processing
- Hybrid networking

CCSP:
- Power efficiency
- Computation vs communication tradeoff compression, coding
- Cooperation, Reductions between problems
- Distributed control
- Interaction of theory & applications
Overview

- Ultimately, sensor network is designed for collecting data and extracting information of physical world
- Network traffic highly depends on processing strategy, and decoupled design of processing and networking may be drastically inefficient

Distributed vs. Centralized Sensing

- **Strengths**
  - Improved robustness by sensor redundancy
  - Improved SNR by sensor’s spatial distribution
- **Weaknesses**
  - Limited battery energy
  - Limited use of sensors
  - Limited wireless bandwidth
- **Energy consumption per bit**
  - Wireless communication cost >> Processing cost
  - Calls for distributed, in-network processing
Two Categories of Signal Processing

- For states of point source(s)
  - Target classification/localization/tracking
- For states of continuum phenomena
  - Micro-climate monitoring
  - Contamination monitoring
- This talk is about point source
  - Beamforming
  - Sensor selection

Beamforming

- Signal received by a sensor is attenuated and delayed copy of source signal plus noise
- Sensors may experience independent noise
- Noise can be canceled out by summation of properly time-shifted sensor signals
- Such *shift & sum* is beamforming
Purpose of Beamforming

- Localization of source
  - Signal time shifts for most constructive summation indicate source location/bearing
- Reconstruction of source signal
  - Properly combined signal has higher SNR than that of any individual sensor
- Sources separation
  - Simultaneous sources can be separated based on difference of their locations/bearings

Categories of Beamforming

- Near-field vs. far-field
  - Near-field: source(s) close to sensor array, source location can be estimated
  - Far-field: source(s) far from sensor array, source bearing can be estimated
- Two-step vs. single-step
  - Two-step: first estimate time shifts, then estimate source location/bearing
  - Single-step: estimate source location/bearing directly from data
Time difference + Least Square beamforming

- Two steps, only for single source
- First, use cross-correlation of sensor signals to estimate time difference of signal arrival among sensors
  - Given two sequence \( x(n), y(n), n = 1, \ldots, N \)
  - \( \text{xcorr}(k) = \sum_{n=1}^{N} x(n)y(n+k) \), \( k = 1, \ldots, 2N-1 \)
- Least square of time difference to estimate source location/bearing
  - Introduce additional variable, source location \( r_s \), to make equation linear

Tung, Yao, Reed, Hudson, Chen, and Chen 1999

A little bit of Math

\[ A y = d, \]

where \[ A = \begin{bmatrix} r_1^T & t_{s1} \\ r_2^T & t_{s2} \\ \vdots & \vdots \\ r_M^T & t_{sM} \end{bmatrix}, \quad y = \begin{bmatrix} r_1^T \\ r_2^T \\ \vdots \\ r_M^T \end{bmatrix}, \quad d = \frac{1}{2} \begin{bmatrix} ||f_1||^2 + ||f'||^2 + t_{s1}^2 \\ ||f_2||^2 + ||f'||^2 + t_{s2}^2 \\ \vdots \\ ||f_M||^2 + ||f'||^2 + t_{sM}^2 \end{bmatrix}. \]

The constraint of unknown vector \( y \) is: \( v^T B y = \| v'^T y \|. \)

where \[ B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad f = [0 \ 0 \ 1]^T. \]

The solution of \( y \) using Lagrangian multiplier is: \( y = (A^TA + \lambda v^TB - \lambda v'^TB)^{-1} A^T d. \)

The Lagrangian multiplier \( \lambda \) can be obtained by substitute the above equation to the constraint.
Aproximate Maximum Likelihood (single source)

Array signal model in time domain:
For a randomly distributed array of $P$ sensors, the data collected by the $p$th sensor at time $n$ is:
$$x_p(n) = a_p s_p(n - t_p) + w_p(n),$$
for $n = 0,...,N - 1$, $p = 1,...,P$, where $a_p$ is the signal gain level of the source at the $p$th sensor. $s_p$ is the source signal, $t_p$ is the fractional time delay in samples ($t_p = |r_p - r_s|/v$).

Array signal model in frequency domain:
$$X(k) = d(k)S_o(k) + \eta(k),$$
where the array data spectrum $X(k) = [X_1(k),...,X_P(k)]^T$, The steering vector:
$$d(k) = [d_1(k),...,d_P(k)]^T,\quad d_p(k) = a_p e^{-j2\pi k t_p},$$
$S_o(k)$ is the source spectrum. $\eta(k)$ is zero mean complex white Gaussian with variance $N\sigma^2$.

AML beamforming (cont.)

Parameter $\Theta = [\theta_s, S_0]$, where $\theta_s$ is source location and $S_0$ is source signal

Maximum likelihood estimate of $\Theta$
$$\max_{\Theta} L(\Theta) = \min_{\theta_s, S_0} \sum_{k=1}^{N/2} \|X(k) - d(k)S_0(k)\|^2$$

Complex search is needed to solve $\Theta$ in the above equation.
Practical issues in Beamforming

- Sensor locations must be known
  - Cooperative node localization
  - Stationary sensor, done once, low cost
- Fine-grained time synchronization is required
  - RBS, up to a few micro seconds
  - Continuous efforts, only sensors in the same beamforming array need tight sync

Testbed: Hardware and OS

- Test bed node is COMPAQ iPAQ H3760 Pocket PC expanded with ORiNOCO silver PC card of 11 Mbps.
- OS is the familiar distribution of Linux under StrongArm SA1100 processors.

Powered by Wang, Yip Maniezzo, Chen, Hudson, Elson, and Yao, 2002
Outdoor Experiment using iPAQ testbed

Results

Chen, Yip, Elson, Wang, Maniezzo, Hudson, Yao, and Estrin, 2003
Sensor Selection for Localization/Tracking

- Incrementally involve relevant sensors to improve belief of target location
- Some sensor is more informative than others
- Using informative sensors reduce number of sensors needed

Sensor Data Fusion Illustration

Grid representation of prior target location PDF $p_{\text{prior}}(x)$ and sensor-data-converted target location PDF $p_f(x)$

Grid representation of posterior target location PDF $p_{\text{posterior}}(x) = c \cdot p_{\text{prior}}(x) + p_f(x)$
Sensor Selection Problem Formulation

- Given
  - Prior probability distribution of target location \( p(x) \)
  - Location, sensing modality, entropy of sensing model \( p(z_i|x) \) of a set of additional sensors
- Find
  - A sensor \( i \) whose data \( z_i \) will yield (almost) the greatest reduction of target location uncertainty
    \[
    \hat{i} = \arg \max_{i \in S} \left( \int p(x|z_i) \log p(x|z_i) dx - \int p(x) \log p(x) dx \right)
    \]
- Constraint
  - Selection decision is made without obtaining actual data of all additional sensors

Mutual Information Based Sensor Selection\[1\][2]

- Actual sensor data \( z_i \) is not available. Some propose to maximize expected entropy reduction w.r.t. predicted \( p(z_i) = p(x)^*p(z_i|x) \)
  \[
  \hat{i} = \arg \max_{i \in S} (H(x) - H(x|z_i))
  \]
- \( H(x) - H(x|z_i) \) is mutual information of \( x \) and \( z_i \)
  \[
  \hat{i} = \arg \max_{i \in S} \int p(x, z_i) \log \frac{p(x, z_i)}{p(x)p(z_i)} dx dz_i
  \]
- Target location \( x \) could be up to 3-D, \( z_i \) could be up to 2-D, above integration could be up to 5-D. Computation could be intensive.

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\[1\] Liu, Reich, and Zhao, 2002
\[2\] Erkin, Fisher, and Potter, 2003
Heuristics to Determine Ability of Uncertainty Reduction*

- $H^v - H^s$ as sensor’s potential of reducing target location uncertainty
  - $H^v$ is entropy of the sensor’s view of the prior target location PDF $p(x)$
  - $H^s$ is entropy of the sensor’s sensing model $p(z|x_0)$, $x_0$ is most likely estimate of target location
- Following slides illustrate concept of $H^v$, and relation between entropy difference $H^v - H^s$ and sensor’s actual ability to reduce target location uncertainty

* Collaborative work of Wang, Yao, Pottie, and Estrin
Different Sensors Have Different Views

S4: $p(x) \Rightarrow$ direction PDF $[-40^\circ, 40^\circ]$

S3: $p(x) \Rightarrow$ direction PDF $[100^\circ, 120^\circ]$

Greater $H^V$ results in Greater Uncertainty Reduction
Sensing Uncertainty

- Smaller sensing uncertainty $H^s$ results in greater reduction of target location PDF uncertainty
- $H^s$ could depend on sensing algorithm, sensor platform, SNR etc. We assume it can be estimated
- if $H^s$ doesn’t change frequently, it could be pre-computed and reused

$H^s$ is entropy of $p(z_i|x_0)$, where $x_0$ is most likely location
Heuristics Evaluation for DOA Sensors

- Gaussian sensing uncertainty
  - S₃, S₄: 2 degrees
  - S₅, 1 degree
- Heuristic potential $H^r - H^s$ of reducing target location uncertainty increases as actual ability increases

More Evaluation of Heuristics
Summary of Sensor Selection Heuristics

- General heuristics across different sensing modality, validated using simulations for DOA, TDOA and range sensors mixed.
- Selection decision making needs no actual data from candidate sensors.
- Computational complexity for 2-D localization:
  - Mutual information based: $3$-D integration of complex kernel, $O(n^3)$
  - Entropy based heuristics: 2-D integration of target location PDF for computing sensor's view, $O(n^2)$

Target Classification

- Focuses on classification at a single node.
- Uses acoustic and seismic spectra of wheeled and tracked targets as feature vectors.
- Extracts feature vectors from time series data using FFT.
- Elements of the feature vectors are the Fourier coefficients (corresponding to the signal power at that frequency).
- Acoustic: Down-sampled to $f_s = 5$kHz, 1000 point FFT, only used 0-1kHz BW, then compressed by 4x and 10x to obtain 50 and 20 element feature vectors.
- Seismic: $f_s = 256$Hz, 256 point FFT using 64 samples and zero padded data segments.
Target Classification (2) – Acoustic PSD

- Power Spectral Density plots of different targets by the same sensor instances
- Note the obvious differences in the prototype signatures, allowing clean separations

Target Classification (3) – Seismic PSD

- Power Spectral Density plots of the same target by different sensor instances
- Note the signature differences in 5a and 5c
- What explains these differences?
Target Classification (4) – Algorithms and Validation

- Three classification algorithms were tested
  - k-Nearest Neighbor
  - Maximum Likelihood Classifier
  - Support Vector Machine
- To cross-validate the performance of the classifiers
  - Available data divided into three sets: F1, F2, F3
  - Take two sets at a time for training and one for testing:
    - Experiment A – Training: F1+F2 training; Testing: F3
    - Experiment B – Training: F2+F3 training; Testing: F1
    - Experiment C – Training: F1+F3 training; Testing: F2

Target Classification (5) – Acoustic Performance

- SVM demonstrates best performance
- K-NN demonstrates next best performance
- ML demonstrates poorest performance

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<tr>
<th>SVM</th>
<th>Tracked</th>
<th>Wheeled</th>
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<tbody>
<tr>
<td>Tracked</td>
<td>887 (92.50%)</td>
<td>72 (7.50%)</td>
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<tr>
<td>Wheeled</td>
<td>55 (5.55%)</td>
<td>1495 (96.45%)</td>
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<th>K-Nearest Neighbor (K = 1)</th>
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Maximum Likelihood (Gaussian Modeling)

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<td>Tracked</td>
<td>779 (81.23%)</td>
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<tr>
<td>Wheeled</td>
<td>171 (11.03%)</td>
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Target Classification (6) – Seismic Performance

- SVM demonstrates best performance
- K-NN demonstrates next best performance
- ML demonstrates particularly poor performance for Wheeled Targets (77.6% correct classification rate)

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<td>K-Nearest Neighbor (K = 1)</td>
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<td>Tracked</td>
<td>197 (89.5%)</td>
<td>23 (10.4%)</td>
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<td>Wheeled</td>
<td>24 (4.80%)</td>
<td>476 (95.2%)</td>
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<td>Maximum Likelihood (Gaussian Modeling)</td>
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<tr>
<td>Tracked</td>
<td>203 (92.27%)</td>
<td>17 (7.73%)</td>
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<tr>
<td>Wheeled</td>
<td>112 (22.4%)</td>
<td>388 (77.6%)</td>
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<td>SVM</td>
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<tr>
<td>Tracked</td>
<td>207 (94.09%)</td>
<td>13 (5.91%)</td>
</tr>
<tr>
<td>Wheeled</td>
<td>15 (3.0%)</td>
<td>485 (97.0%)</td>
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Issues and Challenges

- Collaborative Signal Processing faces many real-world hurdles
  - Uncertainty in temporal and spatial measurements
    - Depends on accuracy of time synchronization
    - Depends on accuracy of network node localization
  - Variability in experimental conditions
    - Classifications assumes that target signatures are relatively invariant
    - Node locations and orientations may results in signature variations
    - Environmental factors may alter signals
    - These *nuisance* parameters and be included in a higher dimension feature vectors at cost of increased processing