Detection, Classification and Tracking
Detection, Classification and Tracking of Targets in Distributed Sensor Networks

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Overview

- Detection: Is there a target?
- Localization: If so, where is it?
- Tracking: Which way is it going?
- Classification: What kind of target is it?
Collaborative Signal Processing

- Distributed processing
  - Raw signal is processed locally. Summary statistics are stored locally and transferred between nodes on-demand.

- On-demand processing
  - No automatic publish-subscribe. Nodes are on standby unless requested by query.

- Information fusion
  - Hierarchical information fusion. Progressively lower bandwidth information over progressively larger regions.

- Multi-Resolution Processing
  - Depending on query, some tasks may require a finer spatial/temporal resolution and others lower.
  - Example: Reliable target detection might be performed with coarse space-time resolution, but classification might require finer space-time processing.
Space-time sampling

- Each object generates a time-varying, space-time signature field that can be sensed by different modalities: acoustic, seismic, thermal
- Density of nodes should be commensurate with rate of spatial variation of phenomenon
- Temporal sampling should be commensurate with required bandwidth
Space-Time Cells

- Cell is unit of processing
- How to select the size of the cells?
  - Velocity of target
  - Rate of variation of field (decay exponent)
- Ideally: dynamically adjust size depending on predictions of above.
Detection and Tracking Framework

- Nodes in boundary cells are kept in the active mode in-order to detect target.
- Manager node for cell determines location of target from energy detector output of nodes.
- Manager predicts location of target from last M locations.
- Predicted positions are activated in advance of the target arrival.
- Once target is detected in the new cell, nodes in previous cell is switched to standby.
Detection Techniques

- Goal: Find a distinct feature that can be used to cheaply (energy-wise) and reliably detect target.

- Amplitude-based
  - Detect if signal energy crosses threshold

- Frequency-based
  - Detect if a particular frequency component is dominant in the signal.
  - Detect if the signal has a high degree of periodicity.
Energy-based Detection

- Each node computes running average of signal power over a window of time.
- Sampling rate determined by target signature bandwidth
- Window size determined by expected signature duration.
- Event detected when energy exceeds threshold

![Graph showing energy over time with threshold](image)
Energy-based Detection (2)

- How to choose threshold?
  - Model noise floor as a Gaussian RV and find its mean and variance from the statistics of background noise.
  - Adjust threshold dynamically so that detector maintains constant false alarm rate

Threshold corresponding to 1% CFAR
Energy-based Detection (3)

- Final output of detector
  - Onset time when detector output exceeded threshold
  - Time of maximum signal energy (closest point of approach - CPA)
  - Detector output at time of CPA.
  - Offset time when detector output falls below threshold.

- Communicate Detections to Manager for cell.
ASIC implementations of Detector

- Periodicity estimation in hardware
  - “What is the degree of periodicity in the signal?”
  - Vehicles have high degree of periodicity

- Detection scheme
  - 1-bit per sample (0 or 1)
  - Auto-correlation-based detector (not explained here)

- Power considerations
  - <1uW power consumption
  - 20,000 times less than power consumption of zigbee radio (~20mW)

A wakeup detector for an acoustic surveillance network: Algorithms and VLSI Implementation: Goldberg, Andreaou et al, Johns Hopkins
Distributed Detection

- Relatively mature research topic
  - Lots of work in early 90s
  - Distributed Detection and Data Fusion - P. Varshney (Springer-Verilag)

- How can a cluster of $n$ nodes reliably combine their detections?
  - Make local decision and aggregate decision
  - Local decision rule being a likelihood ratio test leads to global optimal solution.
Localization

- Manager of cell combines detections to localize target
  - Available: signal power detected at different node locations
- Assuming isotropic propagation and exponential attenuation for the target energy source,
  \[ y_i(t) = \frac{s(t)}{\|r(t) - r_i\|^\alpha} \]
- Compute ratios \( y_i(t)/y_j(t) \) to eliminate the unknown \( s(t) \).
  - \( n-1 \) independent equations
  - Solve for unknown target location using non-linear Least Squares
Tracking

- Given target locations at past instants, fit data samples into dynamic model to predict future locations.
  - Assume simple linear/polynomial motion model
- Is reality that simple?
  - Variation in propagation delay between sources of same modality
  - Signal strength may be function of direction
  - Inter-target interference
Classification: What kind of target is this?

- Pick a set of features that distinguish each kind of target.
  - More specific set of features than detection!
  - Why spectral features.
    - Dominant effect consists of periodic components of vehicles. Rotating machinery (engine, gear, wheel) and tread-road impact on seismic/acoustic signatures
  - Which spectral feature?
    - FFT based Power Spectral Density
- Compare classification algorithms
  - k- nearest neighbor (non-parametric), Max-likelihood (parametric), Support Vector Machines
Target Classification: Seismic 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 – Acoustic PSD

Wheeled Vehicle

Tracked Vehicle

Figure 5a: Acoustic PSD of a wheeled vehicle (08020830 DW)

Figure 5b: Acoustic PSD of a tracked vehicle (08030800 AAF)

Power Spectral Density plots of the same target by different sensor instances
Target Classification (4) – Algorithms and Validation

- Three classification algorithms were tested
  - k-Nearest Neighbor
  - Maximum Likelihood Classifier
  - Support Vector Machine

- Details of the classifiers not discussed here

- 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 – Acoustic Performance

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

### K-Nearest Neighbor (K = 1)

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<thead>
<tr>
<th></th>
<th>Tracked</th>
<th>Wheeled</th>
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<tbody>
<tr>
<td>Tracked</td>
<td>842 (87.80%)</td>
<td>117 (12.20%)</td>
</tr>
<tr>
<td>Wheeled</td>
<td>89 (5.74%)</td>
<td>1461 (94.26%)</td>
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### Maximum Likelihood (Gaussian Modeling)

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<tbody>
<tr>
<td>Tracked</td>
<td>779 (81.23%)</td>
<td>180 (18.77%)</td>
</tr>
<tr>
<td>Wheeled</td>
<td>171 (11.03%)</td>
<td>1379 (88.97%)</td>
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### SVM

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<tr>
<td>Tracked</td>
<td>887 (92.50%)</td>
<td>72 (7.5%)</td>
</tr>
<tr>
<td>Wheeled</td>
<td>55 (3.55%)</td>
<td>1495 (96.45%)</td>
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Target Classification – 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)

### SVM

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<tr>
<td>Tracked</td>
<td>197 (89.55%)</td>
<td>23 (10.45%)</td>
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<tr>
<td>Wheeled</td>
<td>24 (4.80%)</td>
<td>476 (95.2%)</td>
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### Maximum Likelihood (Gaussian Modeling)

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<tr>
<td>Tracked</td>
<td>203 (92.27%)</td>
<td>17 (7.73%)</td>
</tr>
<tr>
<td>Wheeled</td>
<td>112 (22.4%)</td>
<td>388 (77.6%)</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 result in signature variations
    - Environmental factors may alter signals
    - These parameters may need to be included in a higher dimension feature vector at cost of increased processing
Challenge: Signal Characteristics Vary for same target

- Signatures for the \textit{same} vehicle differ at different points in space and different sensor nodes.
  - Combine classifiers for better detection
  - Add more sensor modalities
Challenges - Doppler Effect

- Doppler Effect on Spectral Signatures
  - Especially since acoustic and seismic have low propagation speeds.
- \textit{Higher frequencies show greater absolute changes in frequency}

\[ f = \frac{f_0}{1 - (v/v_0) \cos \alpha} \]
Classifying Multiple Targets

- Association Problem: Matching detections to targets
- Very hard problem unless
  - sufficient separation in time (targets arrive at different times at the same node) OR
  - Sufficient separation in space - Targets are detected at different nodes at the same time
- Paper focuses on the single target problem.
Future Research

- Key directions
  - Move toward more collaborative algorithms
  - Extend feature space to higher dimensions
- Intra-sensor collaboration: modal fusion
  - Combine information from multiple sensors in single node
- Inter-sensor collaboration: centralized processing
  - Report raw time series data or statistics to a “central” node
- Doppler-based composite hypothesis testing
  - Incorporate target velocity, CPA distance, and angle between secant and radius (vertex is target’s position)
Remarks

- Paper focuses on classification. Tracking problem is mostly conceptual (although there are some interesting ideas)
- No simulations or empirical evidence supporting single or multiple target tracking
- Hardest problem in classification is multi-target classification
  - Overlapping signatures (disambiguation problem)
  - Tracking multiple targets
- Max signal does not always occur at CPA
How to model event-based systems

- Detection: Low-power (threshold-based)
  - P (false positive)
  - P (false negative)

- Localization
  - Time of flight, angle of arrival, signal power
  - Location estimate + error distribution

- Tracking
  - Use location to determine track
  - Uncertainty: location uncertainty + track uncertainty

- Classification
  - Multiple modalities. Find distinguishing features
  - P (false positive)
  - P (false negative)