II.4 Data Fusion in IoT WSN

Assoc. Prof. Tham Chen Khong
Dept of ECE, NUS

Collaborative Signal Processing (CSP)

- In principle, more information about a phenomenon can be gathered from multiple measurements
  - Multiple sensing modalities (acoustic, seismic, etc.)
    Sound vibration
  - Multiple nodes
- Limited local information gathered by a single node necessitates CSP
  - Inconsistencies between measurements, such as due to malfunctioning nodes, can be resolved
- Variability in signal characteristics and environmental conditions necessitates CSP
  - Complementary information from multiple measurements can improve performance

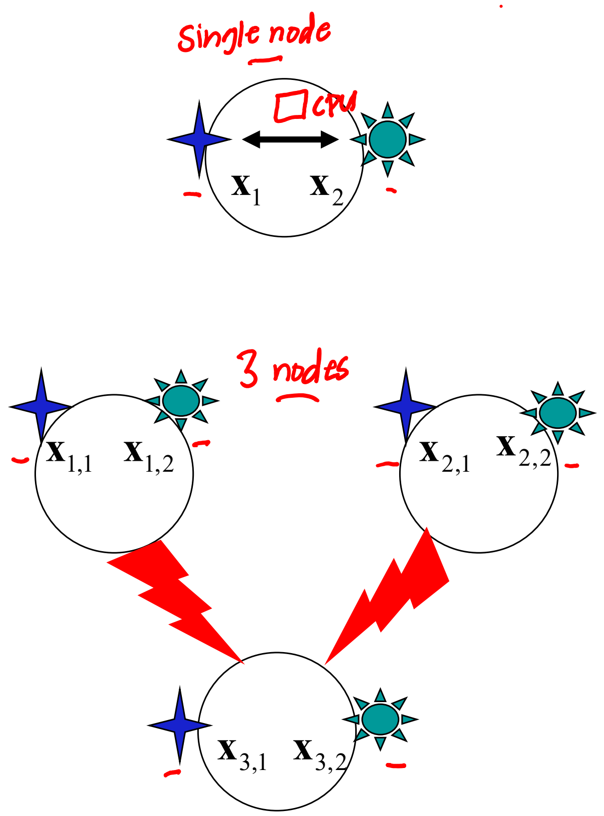
Reference

- [Brooks03] R. Brooks, P Ramanathan and A.K. Sayeed, “Distributed Target Classification and Tracking in Sensor Networks”, Proceedings of IEEE, vol. 91, no. 8, Aug 2003.

Categorization of CSP Algorithms Based on Communication Burden

- Intra-node collaboration
  - Multiple sensing modalities
    - E.g., combining acoustic and seismic measurements
  - No communication burden since collaboration is at a particular node
    - Higher computational burden at the node

more than 1 node
- Inter-node collaboration
  - Combining measurements at different nodes
  - Higher communication burden since data is exchanged between nodes
  - Higher computational burden at manager node

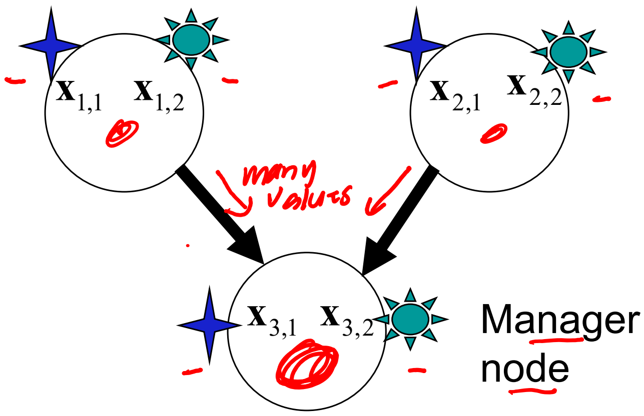


Manager node

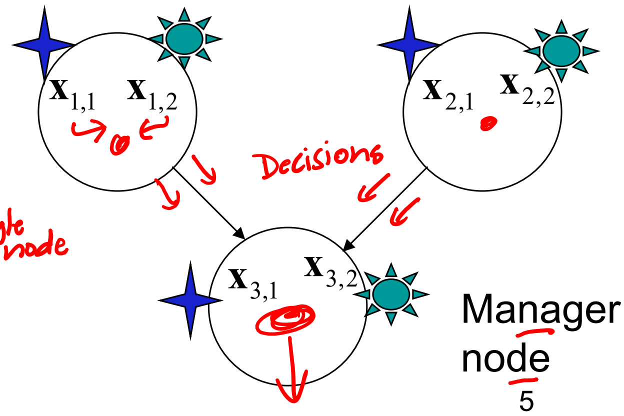
2

Categorization of CSP Algorithms Based on Computational Burden

(a) • Data fusion — do not summarize measurements
- Time series for different measurements are combined
- Higher computational burden since higher dimensional data is jointly processed
- Higher communication burden if different measurements from different nodes



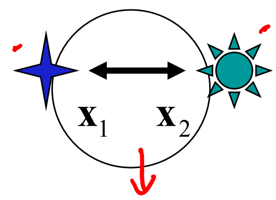
(b) • Decision fusion
- Decisions (hard or soft) based on different measurements are combined
- Lower computational burden since lower dimensional data (decisions) is jointly processed
- Higher communication burden (compared to single node) if the component decisions are made at different nodes



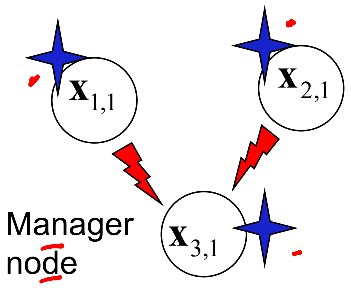
Various Forms of CSP

Combine the 2 categorizations above

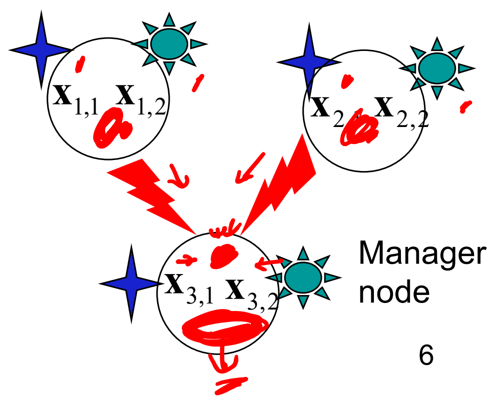
- Single Node, Multiple Modality (SN, MM)
  - Simplest form of CSP: no communication burden
    - Decision fusion
    - Data fusion (higher computational burden)



- Multiple Node, Single Modality (MN, SM)
  - Higher communication burden
    - Decision fusion
    - Data fusion (higher computational burden)



- Multiple Node, Multiple Modality (MN, MM)
  - Highest communication and computational burden
    - i • Decision fusion across modalities and nodes
    - ii • Data fusion across modalities, decision fusion across nodes
    - iii • Data fusion across modalities and nodes



Single Target Classification: Overview

I
- Single measurement classifiers
  - MAP/ML Gaussian classifiers
  - NN classifiers (benchmark) — Nearest Neighbour
  - "Training" and Performance Evaluation
  - Confusion matrices

II
- Multiple measurement classifiers — CSP
  - Data fusion (dependent measurements) (in depth)
  - Decision fusion (independent measurements) (not in depth)
- Different possibilities for CSP-based classification
  - Single node, multiple sensing modalities (SN, MM)
  - Multiples nodes, single sensing modality (MN, SM)
  - Multiple nodes, multiple sensing modalities (MN, MM)

The basic ideas illustrate general CSP principles in distributed decision making

I

Single Measurement Classifier

e.g. M=3

- M possible target classes: $\omega_m \in \Omega = \{m = 1, \cdots, M\}$

bird w_1 cat w_2 dog w_3

accelerometer $\begin{bmatrix} x \\ y \\ z \end{bmatrix}$ N=3

- **x** : N-dim. ~~(complex-valued)~~ real event feature vector
  - **x** belongs to m-th class with probability $P(\omega_m)$
- C: classifier assigns one of the classes to **x**

Maximum A Posteriori

e.g. 2 — e.g. $P(w_2|x)$ is max

MAP: $C(\mathbf{x}) = m \quad \text{if} \quad P(\omega_m \mid \mathbf{x}) = \max_{j=1,\cdots,M} P(\omega_j \mid \mathbf{x})$

$P(w_1|x)$? $P(w_2|x)$? $P(w_3|x)$?

e.g. 1/2/3 — likelihood — prior — A — B

Bayes rule: $C(\mathbf{x}) = \arg\max_{j=1,\cdots,M} \underbrace{P(\mathbf{x} \mid \omega_j)}_{\text{likelihood}} \underbrace{P(\omega_j)}_{\text{prior}}$

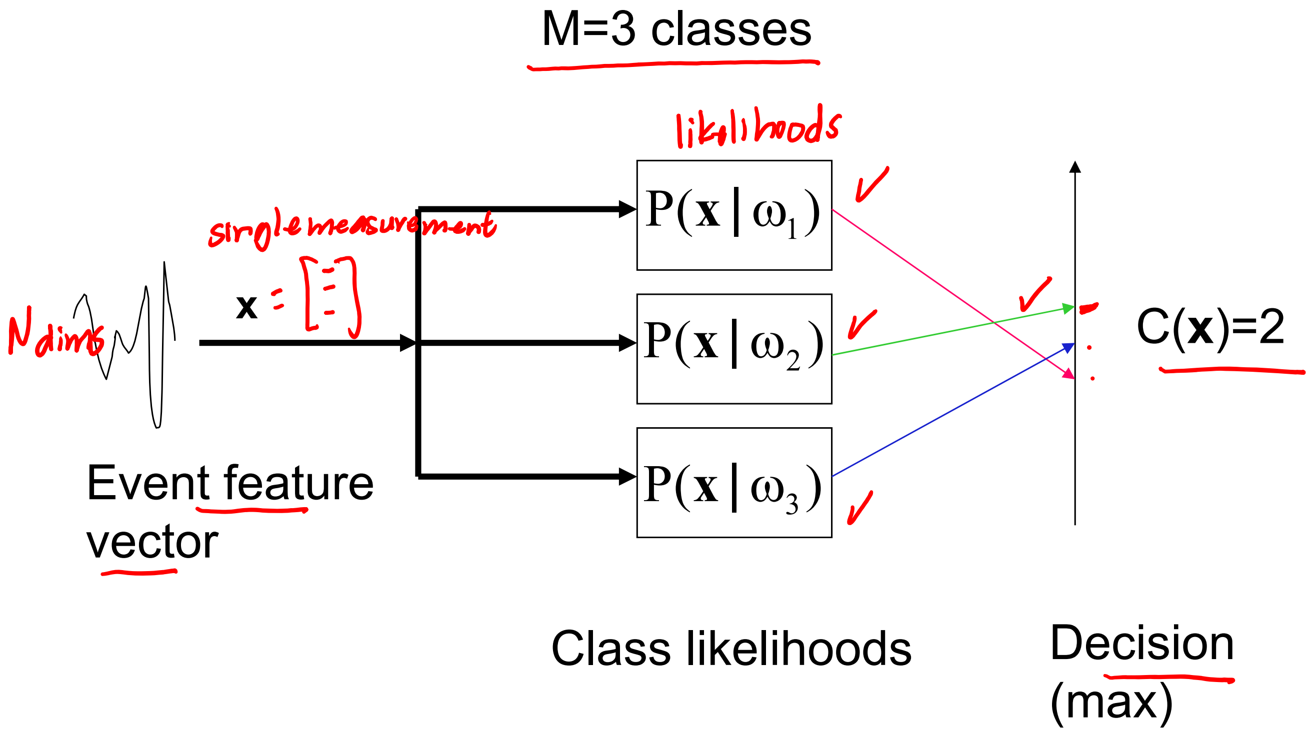
Bayes Theorem $P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$?

Maximum Likelihood

$$\boxed{\text{Equal priors (ML): } \; C(\mathbf{x}) = \arg\max_{j=1,\cdots,M} P(\mathbf{x} \mid \omega_j)}$$

$P(w_1)=P(w_2)=P(w_3)$?

Single Measurement Classifier – Pictorially



Gaussian Classifiers

aka Normal

- Assume that for class j, $\mathbf{x}$ has a Gaussian distribution with mean vector $\boldsymbol{\mu}_j = E_j[\mathbf{x}]$ and covariance matrix
$$\boldsymbol{\Sigma}_j = E_j[(\mathbf{x}-\boldsymbol{\mu}_j)(\mathbf{x}-\boldsymbol{\mu}_j)^T]$$
  - $\boxed{E_j[\bullet]}$ denotes ensemble average over class j
  - Superscript T denotes transpose

- Likelihood function for class j

multi-variate

$$\boxed{P(\mathbf{x}|\omega_j) = \frac{1}{\pi^N|\boldsymbol{\Sigma}_j|}\exp[-(\mathbf{x}-\boldsymbol{\mu}_j)^T\boldsymbol{\Sigma}_j^{-1}(\mathbf{x}-\boldsymbol{\mu}_j)]}$$

Take log

$$-\log P(\mathbf{x}|\omega_j) = \log|\boldsymbol{\Sigma}_j| + \left(\mathbf{x}-\boldsymbol{\mu}_j\right)^T\boldsymbol{\Sigma}_j^{-1}(\mathbf{x}-\boldsymbol{\mu}_j)$$

" Training " and Performance Assessment

labelled bird bird cat

- N^{Tr} training events available for each class
- 3-way cross validation – partition data into 3 sets (S_1, S_2, S_3) with equal number of events for each class
- Three sets of experiments: Train 3 classifiers, choose best

Train	Test
S_1, S_2	S_3

Train	Test
S_1, S_3	S_2

Train	Test
S_2, S_3	S_1

Training and Testing

- In each experiment we have:
  1 – Training phase: estimate mean and covariance for each class from the two training data sets ref S_1, S_2, S_3 above

For $\mathbf{x}_n \in \omega_j \qquad j = 1, \ldots, M$

$$\boxed{\hat{\boldsymbol{\mu}}_j} = \frac{1}{N_0} \sum_{n=1}^{N_0} \mathbf{x}_n \qquad \boxed{\hat{\boldsymbol{\Sigma}}_j} = \frac{1}{N_0} \sum_{n=1}^{N_0} (\mathbf{x}_n - \boldsymbol{\mu}_j)(\mathbf{x}_n - \boldsymbol{\mu}_j)^T$$

N_0 is # items in class j

  2 – Testing phase: Using $(\hat{\boldsymbol{\mu}}_j, \hat{\boldsymbol{\Sigma}}_j)$ estimated from the two training data sets, test the performance of the classifier on the third testing set

ML classifier $$C(\mathbf{x}) = \arg \max_{j=1,\cdots,M} P(\mathbf{x} \mid \omega_j)$$

Confusion Matrix (multi-class)

Classifier output

$C(\mathbf{x})$ / ω_m	1 Bird	2 Cat	…	M Dog
1 Bird	n_{11} ✓ 6	n_{12} 2		n_{1M} 4
2	n_{21}	n_{22}		n_{2M}
:			…	
M Dog	n_{M1} 1	n_{M2} 1		n_{MM} 10

e.g. 12 in test set

Actual classes

true/actual class — classifier o/p

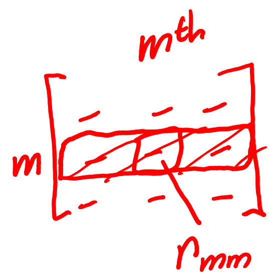
$$[\mathbf{CM}]_{ij} = n_{ij} = \text{number of events from } \omega_i \text{ classified as } \omega_j$$

Probability of Detection, Probability of False Alarm, ~~Belief~~

Performance Metrics of a Classifiers

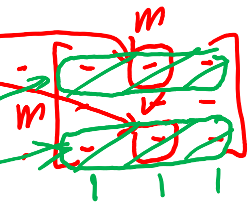
- Probability of detection for class m

$$PD_m = \frac{n_{mm}}{\sum_{j=1}^{M} n_{mj}} \qquad \text{(m-th row)}$$



- Probability of false alarm for class m

$$PFA_m = \frac{\sum_{k=1,k\neq m}^{M} n_{km}}{\sum_{k=1,k\neq m}^{M} \sum_{j=1}^{M} n_{kj}}$$



- ~~Prior belief in the classifier decisions (via training)~~

$$P(\mathbf{x} \in \omega_m \mid C(\mathbf{x}) = j) = \frac{n_{mj}}{\sum_{i=1}^{M} n_{ij}} \qquad \text{(j-th column)}$$

Binary Classification

Confusion Matrix for Binary Classification

classifier output

	$\hat{P}$ (predicted)	$\hat{N}$ (predicted)
10 P positive (actual)	TP 9	FN 1
10 N negative (actual)	FP 1	9 TN

Sensitivity/ Recall ~ Prob Det of Positive class
TP/(TP+FN)

Specificity Prob Det of Neg class
TN/(TN+FP)

Precision
TP/(TP+FP)

Accuracy
(TP+TN)/(TP+TN+FP+FN)
18 / 20
90%

Benchmark: Nearest Neighbor (NN) Classifier

labelled bird ...

- S^{Tr} -- the set of all training event feature vectors $\mathbf{x}^{Tr}$ (containing all classes)

- $\mathbf{x}$ -- test event feature vector to be classified

bird? cat? dog? (1, 2, 3) distance

$$C_{NN}(\mathbf{x}) = \text{class}\left(\arg\min_{\mathbf{x}^{Tr}\in S^{Tr}} \left\|\mathbf{x}-\mathbf{x}^{Tr}\right\|\right)$$

x^{Tr}

That is, find the *training feature vector* that is closest to the *test feature vector*. Assign the label of the closest training feature vector to the test event

II

Multiple Measurements

- K measurements (from a detected event)
  - Different nodes or sensing modalities

- $\mathbf{x}_k$ -- event feature vector for k-th measurement

- Classifier C assigns one of the M classes to the K event measurements $\{\mathbf{x}_1, \cdots, \mathbf{x}_K\}$

different measurements

ML $$C(\mathbf{x}_1, \cdots, \mathbf{x}_K) = \arg\max_{j=1,\cdots,M} P(\omega_j \mid \mathbf{x}_1, \cdots, \mathbf{x}_K)$$

$$\boxed{\text{Equal priors (ML):} \quad C(\mathbf{x}_1, \cdots, \mathbf{x}_K) = \arg\max_{j=1,\cdots,M} P(\mathbf{x}_1, \cdots, \mathbf{x}_K \mid \omega_j)}$$

likelihood

Data Fusion – Gaussian Classifier

- Assume that different measurements $(\{\mathbf{x}_1, \cdots, \mathbf{x}_K\})$ are jointly Gaussian and *correlated*

For $\omega_j, j = 1, \cdots, M$

the concatenated event feature vector (KN dim.)

is Gaussian with mean and covariance:

$$\mathbf{x}^c = \underbrace{\begin{bmatrix} \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_K \end{bmatrix}}_{KN} \quad \text{N dims}$$

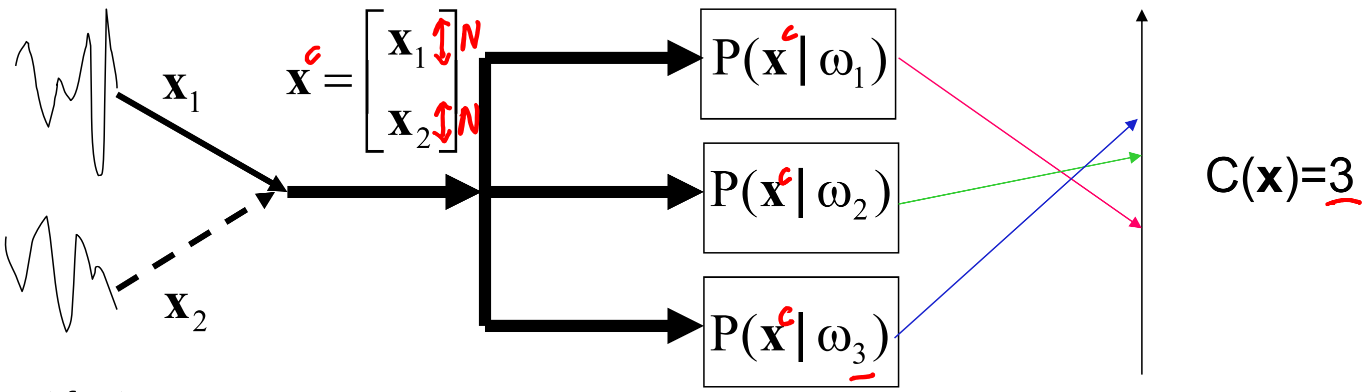
$$\boldsymbol{\mu}_j^c = E_j[\mathbf{x}^c] = \underbrace{\begin{bmatrix} \boldsymbol{\mu}_{j,1} \\ \vdots \\ \boldsymbol{\mu}_{j,K} \end{bmatrix}}_{KN} \qquad \boldsymbol{\Sigma}_j^c = E_j[(\mathbf{x}^c - \boldsymbol{\mu}_j^c)(\mathbf{x}^c - \boldsymbol{\mu}_j^c)^T] = \underbrace{\overset{KN}{\begin{bmatrix} \boldsymbol{\Sigma}_{j,11}, \cdots, \boldsymbol{\Sigma}_{j,1K} \\ \vdots \\ \boldsymbol{\Sigma}_{j,K1}, \cdots, \boldsymbol{\Sigma}_{j,KK} \end{bmatrix}}}_{KN}$$

N

$(\boldsymbol{\mu}_j^c, \boldsymbol{\Sigma}_j^c)$ characterize the j-th class and can be estimated from training data ➔ cross-validation, CM's, PD, PFA, ~~belief~~

Multiple Measurement Classifier – Data Fusion

M=3 classes



Event feature vectors from 2 measurements

Concatenated event feature vector

Class likelihoods

Decision (max)

Higher computational burden

Data Fusion – NN Classifier

- Let S^{Tr} denote the set of all *concatenated* training event feature vectors $\mathbf{x}^{cTr}$ (containing all classes)

$$\mathbf{x}^{cTr} = \begin{bmatrix} \mathbf{x}_1^{Tr} \\ \vdots \\ \mathbf{x}_K^{Tr} \end{bmatrix} \qquad \text{(NK dimensional)}$$

- Let $\mathbf{x}^c$ denote the concatenated test event feature vector to be classified

$$C_{NN}(\overbrace{\mathbf{x}_1, \cdots, \mathbf{x}_k}^{x^c}) = \text{class}\left(\arg \min_{\mathbf{x}^{cTr} \in S^{Tr}} \left\| \mathbf{x}^c - \mathbf{x}^{cTr} \right\| \right)$$

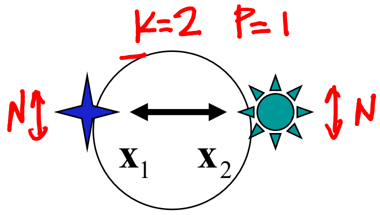
Forms of Data Fusion in CSP

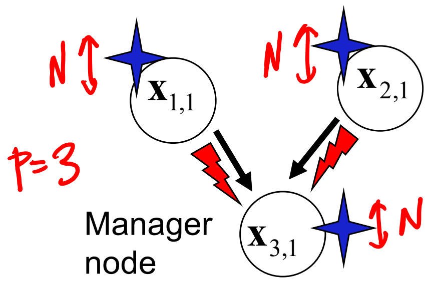
K modalities, P nodes

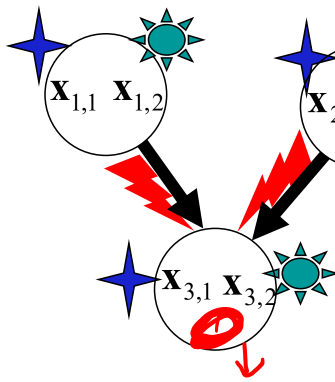
- Data fusion of multiple modalities (e.g, acoustic and seismic) at each node (SN, MM)
  - Higher comp. burden (NK dim. data)
  - No additional comm. burden

P>1

- Data fusion of a single modality at multiple nodes (MN, SM)
  - Higher computational burden at manager node (PN dim. data)
  - Higher communication burden due to transmission of N dim. data from different nodes to the manager node
- Data fusion of multiple modalities at multiple nodes (MN, MM)
  - Highest computational burden at manager node (NKP dim. data)
  - Highest communication burden due to transmission of KN dim. multi-modality data from different nodes to the manager node







Pros and Cons of Data Fusion

- Pros
  - Maximal exploitation of available information in multiple time~~s~~ series
  - Potentially the best performing classification scheme
- Cons
  - High computational burden
  - High communication burden if data fusion across nodes
  - Need larger amount of data for "training"
  - Inconsistencies between measurements could cause performance degradation (e.g. malfunctioning nodes)
- In contrast, **Decision Fusion**:
  - has lower computational and communication burden
  - however, different measurements have to be independent or uncorrelated (not covered here)

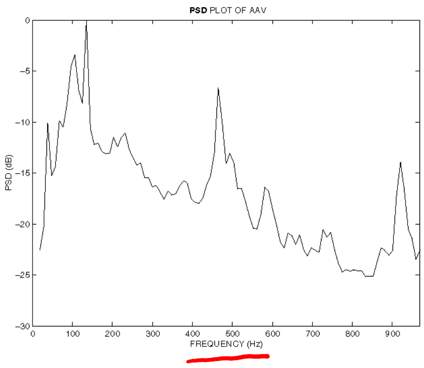
Experiments: Seismic Feature Characteristics

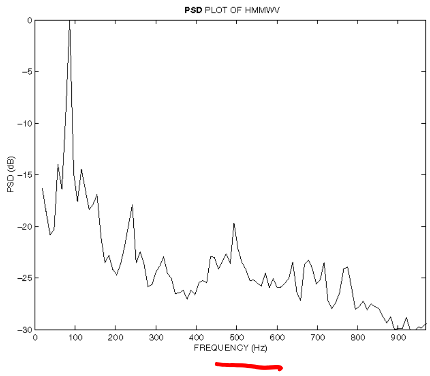
- Seismic signals
  - Sampling rate reduction from 4960 Hz to 512 Hz
  - 512-pt FFT of 512-sample (256-overlap) segments
    - 1 Hz resolution
  - The first 100 positive frequency FFT samples used (100 Hz)
  - 2-pt averaging of the 100 FFT samples yields the final N=50 dimensional FFT feature vectors
    - 2 Hz resolutions
  - About 10-50 feature vectors in each event depending on the vehicle
    - Event feature vector matrix **X** is 50x10 to 50x50
    - 50 dimensional mean event feature vectors **x**
- Complex or absolute value FFT features

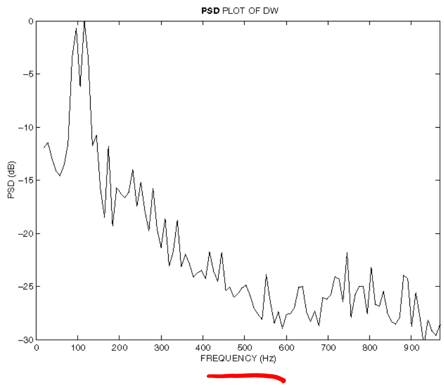
Class Descriptions

- Tracked vehicle class: AAV (Amphibious Assault Vehicle)
- Wheeled vehicle class: DW (Dragon Wagon) and HMWV (Humvee)
- Locomotion Class and Vehicle Class classification
- Approximately equal number of training and testing events for all classes
- 3-way cross validation for performance assessment

Representative Acoustic FFT Features







AAV – tracked
(Amphibious
Assault Vehicle)

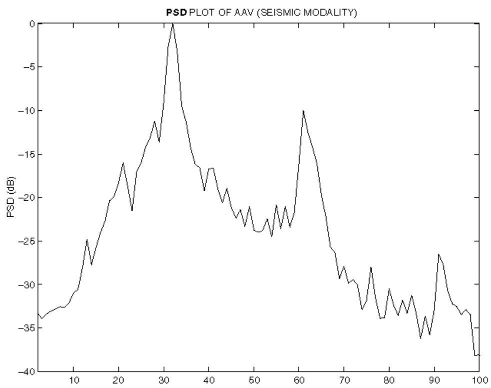
HMV – wheeled
(Humvee)

DW – wheeled
(Dragon Wagon)

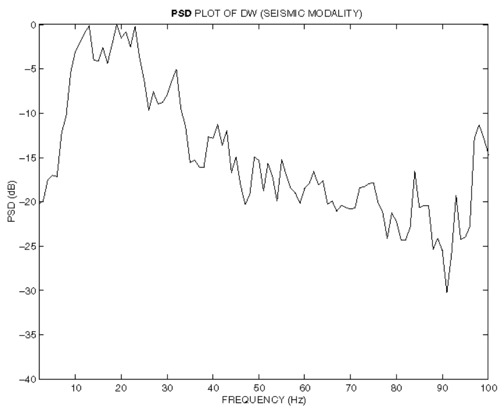
SITEX02 Data. DARPA SenseIT Program

Representative Seismic FFT Features

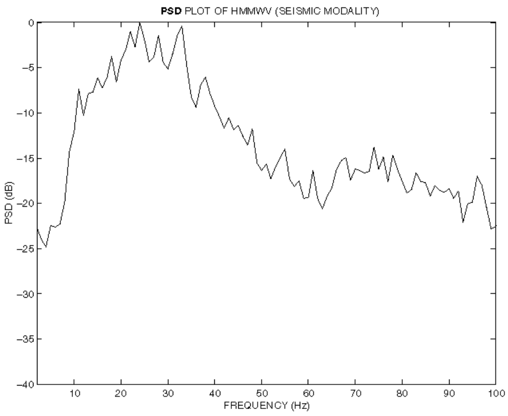
(a)



(b)



(c)



a) AAV (tracked)
b) DW (wheeled)
c) HMMWV (wheeled)

SITEX02 Data. DARPA SenseIT Program

1. # Single Node Single Modality (SN, SM) – Locomotion Class

No Data Fusion

Absolute-value FFT acoustic features

Gaussian Classifier

CM

Classifier

Actual

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	109	11
Tracked	22	98

120

120

not wheeled

109/120

PD = 0.91, 0.82, Ave = 0.86

22/120

PFA = 0.18, 0.09

NN Classifier (benchmark)

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	102	18
Tracked	1	119

PD = 0.85, 0.99, Ave = 0.92

PFA = 0.01, 0.15

120 events for each class

2. # Single Node Single Modality (SN, SM) – Vehicle Class

Absolute-value FFT acoustic features

Gaussian Classifier

ω_m \ C(**X**)	AAV	DW	HMV
AAV	53	5	2
DW	12	42	6
HMV	15	14	31

PD = 0.88, 0.70, 0.52, Ave = 0.70

PFA = 0.22, 0.16, 0.07

NN Classifier (benchmark)

ω_m \ C(**X**)	AAV	DW	HMV
AAV	43	9	8
DW	0	49	11
HMV	1	13	46

PD = 0.72, 0.82, 0.77, Ave = 0.77

PFA = 0.01, 0.18, 0.16

60 events for each vehicle

3

Single Node Multiple Modality (SN, MM)
Data Fusion – Locomotion Class

Acoustic and seismic features

Gaussian Classifier

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	117	3
Tracked	25	95

PD = 0.97, 0.80, Ave = 0.88

PFA = 0.21, 0.02

NN Classifier (benchmark)

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	106	14
Tracked	4	116

PD = 0.88, 0.97, Ave = 0.92

PFA = 0.03, 0.12

120 events for each class

4

Single Node Multiple Modality (SN, MM)
Data Fusion – Vehicle Class

Acoustic and seismic features

Gaussian Classifier

ω_m \ C(**X**)	AAV	DW	HMV
AAV	59	0	1
DW	9	46	5
HMV	25	12	23

PD = 0.98, 0.77, 0.38, Ave = 0.71

PFA = 0.28, 0.10, 0.05

NN Classifier (benchmark)

ω_m \ C(**X**)	AAV	DW	HMV
AAV	43	6	11
DW	0	47	13
HMV	1	22	37

PD = 0.72, 0.78, 0.62, Ave = 0.71

PFA = 0.01, 0.23, 0.20

60 events for each vehicle

5

Comparison of Various Forms of CSP – Locomotion Class

Gaussian Classifier

(SN, SM)

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	109	11
Tracked	22	98

PD = 0.91, 0.82,
Ave = 0.86

PFA = 0.18, 0.09

(SN, MM) – Data Fusion

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	117	3
Tracked	25	95

PD = 0.97, 0.80,
Ave = 0.88

PFA = 0.21, 0.02

(SN, MM) – Dec. Fusion

ω_m \ C(**X**)	Wheeled	Tracked
Wheeled	110	10
Tracked	32	88

PD = 0.92, 0.73,
Ave = 0.83

PFA = 0.27, 0.08

6.

Comparison of Various Forms of CSP – Vehicle Class

Gaussian Classifier

(SN, SM)

ω_m \ C(**X**)	AAV	DW	HMV
AAV	53	5	2
DW	12	42	6
HMV	15	14	31

PD = 0.88, 0.70, 0.52,
Ave = 0.70

PFA = 0.22, 0.16, 0.07

(SN, MM) – Data Fusion

ω_m \ C(**X**)	AAV	DW	HMV
AAV	59	0	1
DW	9	46	5
HMV	25	12	23

PD = 0.98, 0.77, 0.38,
Ave = 0.71

PFA = 0.28, 0.10, 0.05

(SN, MM) – Dec. Fusion

ω_m \ C(**X**)	AAV	DW	HMV
AAV	55	5	0
DW	8	44	8
HMV	20	13	27

PD = 0.92, 0.73, 0.45,
Ave = 0.70

PFA = 0.23, 0.15, 0.07

Inconsistencies between modalities are present

Challenges

- Uncertainty in temporal and spatial measurements critically affects estimation:
  - Uncertainty in node locations
  - Uncertainty in timing and synchronization
- Variability in signal characteristics:
  - Doppler shifts due to motion
  - Gear shifts, acceleration in vehicles
- Variability in environmental/sensor conditions:
  - Most algorithms exploit prior statistical information about sources
  - Observed statistical characteristics can vary markedly depending on environmental conditions, such as terrain, foliage, rain, wind etc.
  - Variability in sensor characteristics (e.g., gain calibration)
- A key challenge is to develop CSP algorithms that are robust to such uncertainty/variability in measurements and conditions

Questions?