II.2 Data Fusion in IoT WSN

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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

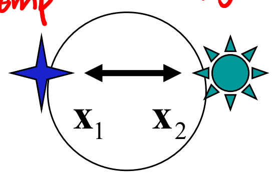
Reference

- [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.

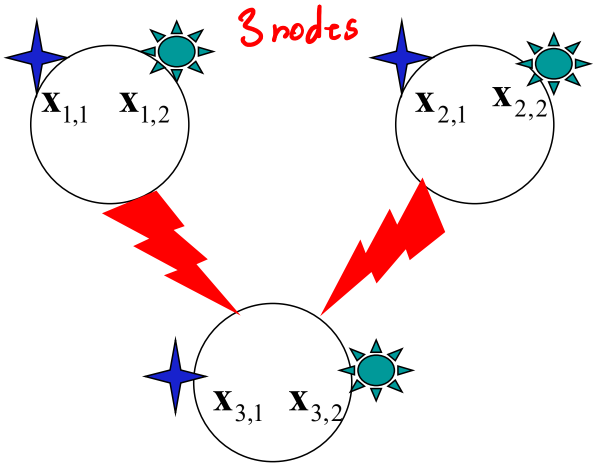
1 Categorization of CSP Algorithms Based on Communication Burden

- Intra-node collaboration (within)
  - 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

e.g. temp
Single node
light



3 nodes

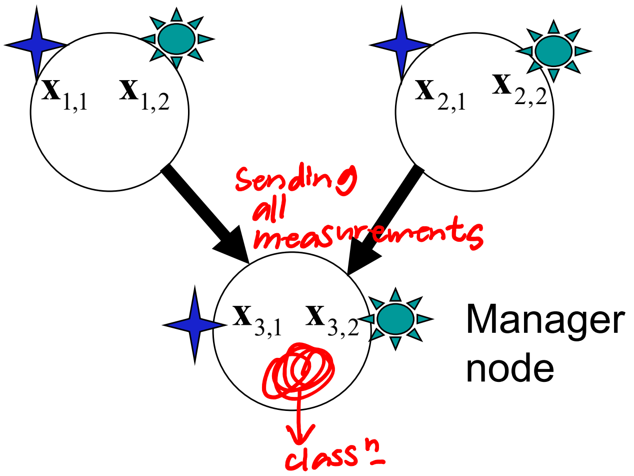


Manager node

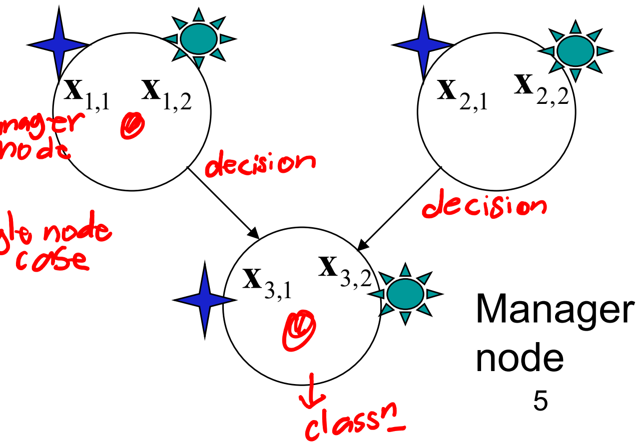
- Inter-node collaboration
  - Combining measurements at different nodes
  - Higher communication burden since data is exchanged between nodes
  - Higher computational burden at manager node

2 Categorization of CSP Algorithms Based on Computational Burden

(a)
- Data fusion
  - 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

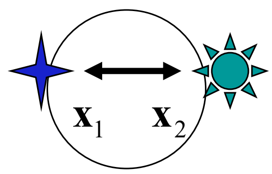


(b)
- Decision fusion
  - Decisions (hard or soft) based on different measurements are combined
  - Lower computational burden since lower dimensional data (decisions) is jointly processed
  at manager node
  - Higher communication burden if the component decisions are made at different nodes
  compared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

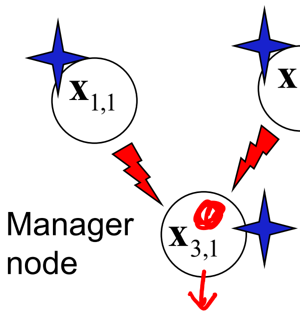


Various Forms of CSP

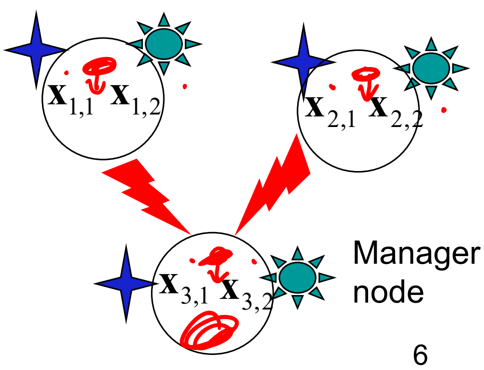
- Single Node, Multiple Modality (SN, MM)
  - Simplest form of CSP: no communication burden
    - Decision fusion
    - Data fusion (higher computational burden)



- 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
    - Decision fusion across modalities and nodes
    - Data fusion across modalities, decision fusion across nodes
    - Data fusion across modalities and nodes



Single Target Classification: Overview

I

- Single measurement classifiers
  - MAP/ML Gaussian classifiers (Max likelihood)
  - 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)
  - Multiple nodes, single sensing modality (MN, SM)
  - Multiple nodes, multiple sensing modalities (MN, MM)

The basic ideas illustrate general CSP principles in distributed decision making

usually to identify event or object

Single Measurement Classifier

I

M=3   e.g. bus   car   motorcycle   1, 2, 3

- M possible target classes: $\omega_m \in \Omega = \{m = 1, \cdots, M\}$
- **x** : N-dim. (~~complex~~ real-valued) 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

MAP: $C(\mathbf{x}) = \underset{1/2/3}{m}$ if $P(\omega_m \mid \mathbf{x}) = \max_{j=1,\cdots,M} P(\overset{A}{\omega_j} \mid \overset{B}{\mathbf{x}})$

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

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

$P(\omega_1) = P(\omega_2) = P(\omega_3)$

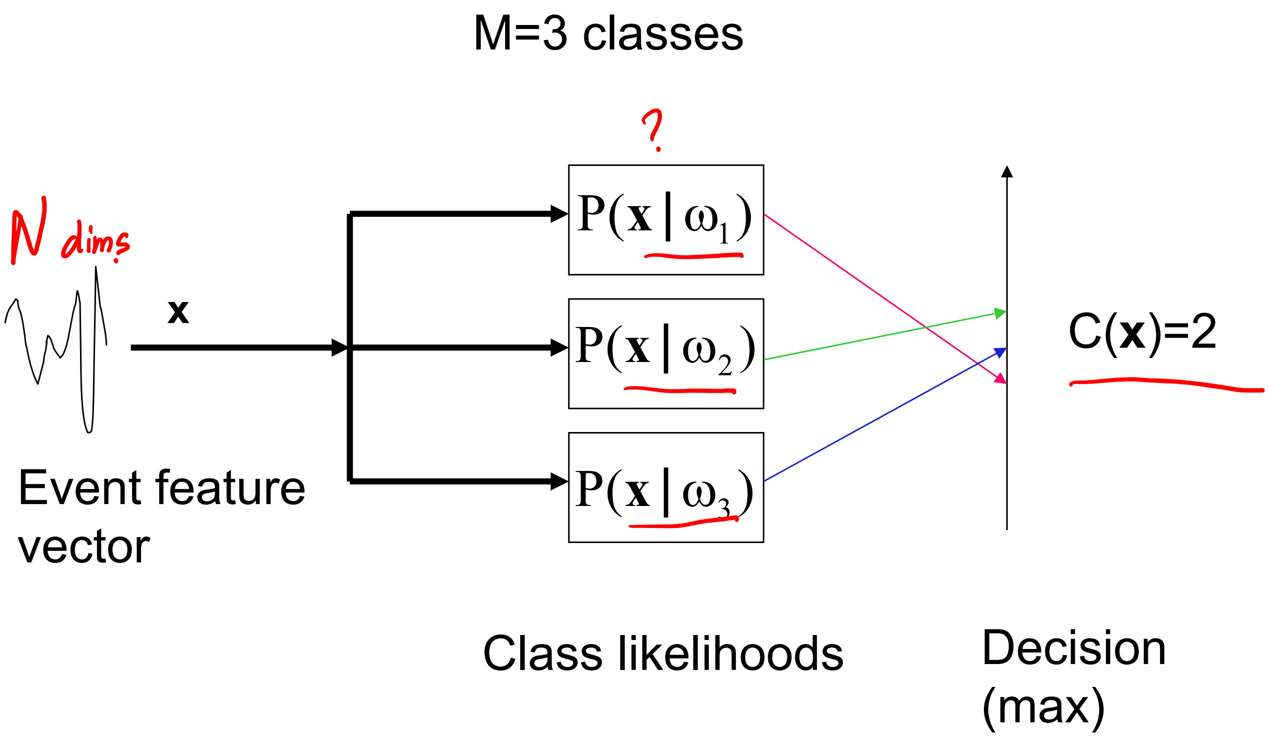
prior

$P(\omega_1 \mid x)$?
$P(\omega_2 \mid x)$?
$P(\omega_3 \mid x)$?

Bayes Theorem: $P(A \mid B) = \frac{P(B \mid A) P(A)}{P(B)}$ (likelihood, prior)

? ✓

Single Measurement Classifier – Pictorially



Gaussian Classifiers

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

- Likelihood function for class j

multi-variable

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

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

Training and Performance Assessment

e.g. $=20$

- N^{Tr} training events available for each class

e.g. total 60 events

- 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	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:
  - Training phase: estimate mean and covariance for each class from the two training data sets

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

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

feature vectors in class j

  - 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

j ?

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

make classification decision for each feature vector x in the 3rd test set

Confusion Matrix (multi-class)

Classifier Decision

$C(\mathbf{x})$ \ ω_m	1	2	…	M
1 20 e.g. Bus	n_{11} 10 ✓	n_{12} 2 ×	6 ×	n_{1M} 2 ×
2 car	n_{21}	n_{22}		n_{2M}
: motor cycle			…	
M	n_{M1}	n_{M2}		n_{MM}

20

Actual class

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

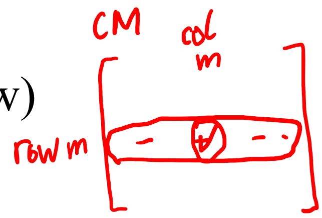
true/actual — classifier decision

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

- Probability of detection for class m

PD

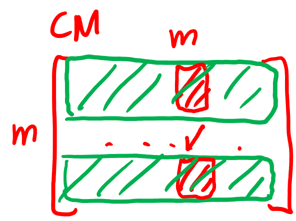
$$\rightarrow \quad PD_m = \frac{n_{mm}}{\sum_{j=1}^{M} n_{mj}} \qquad \text{(m-th row)}$$



- Probability of false alarm for class m

PFA

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



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

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

Binary Classification

Confusion Matrix for Binary Classification

numbers

	$\hat{\mathrm{P}}$ positive (predicted)	$\hat{\mathrm{N}}$ negative (predicted)	
P positive (actual) 20	e.g. 18 TP ✓	2 FN	Sensitivity/ Recall TP/(TP+FN) PD for P class
N negative (actual) 20	FP 3	17 TN ✓	Specificity TN/(TN+FP) PD for N class
	Precision TP/(TP+FP)	Accuracy (TP+TN)/(TP+TN+FP+FN)	

Benchmark: Nearest Neighbor (NN) Classifier

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

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

e.g. 1 $\quad x^{Tr}$: 1 $\quad$ distance

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

?

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 $\{\mathbf{x}_1, \cdots, \mathbf{x}_K\}$

K measurements 1? 2? ...

new

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

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

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:

$$\mathbf{x}^c = \begin{bmatrix} \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_K \end{bmatrix} \quad \text{KN} \; (\text{N each})$$

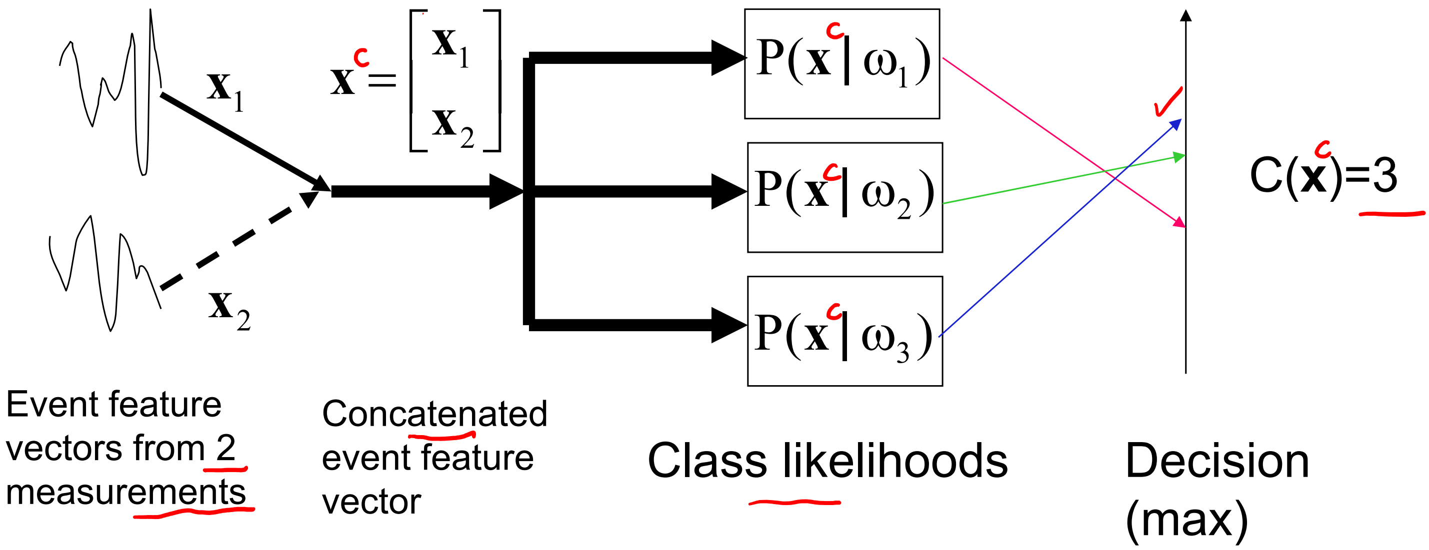
$$\mu_j^c = E_j[\mathbf{x}^c] = \begin{bmatrix} \mu_{j,1} \\ \vdots \\ \mu_{j,K} \end{bmatrix} \quad \text{KN} \; (\text{N each})$$

$$\Sigma_j^c = E_j[(\mathbf{x}^c - \mu_j^c)(\mathbf{x}^c - \mu_j^c)^T] = \begin{bmatrix} \Sigma_{j,11}, \cdots, \Sigma_{j,1K} \\ \vdots \\ \Sigma_{j,K1}, \cdots, \Sigma_{j,KK} \end{bmatrix} \quad \text{KN} \times \text{KN}$$

(μ_j^c, Σ_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



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

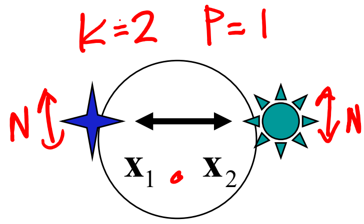
$$C_{NN}(\mathbf{x}_1, \cdots, \mathbf{x}_k) = \text{class}\left(\arg \min_{\mathbf{x}^{cTr} \in S^{Tr}} \overbrace{\left\| \mathbf{x}^c - \mathbf{x}^{cTr} \right\|}^{\text{distance}}\right)$$

Note: meaning of K is different

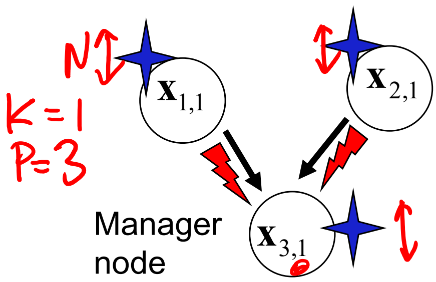
Forms of Data Fusion in CSP

K modalities, P nodes

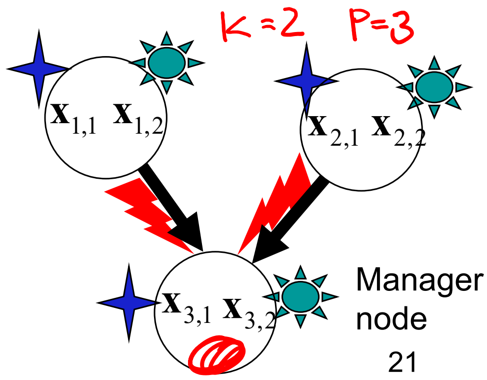
- Data fusion of multiple modalities (e.g, acoustic and seismic) at each node (SN, MM)
  - Higher comp. burden (NK dim. data)
  - No additional comm. burden



- 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 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)

usually not satisfied

in practice, still not too bad

Experiments:
Seismic Feature Characteristics

vibration

- 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**

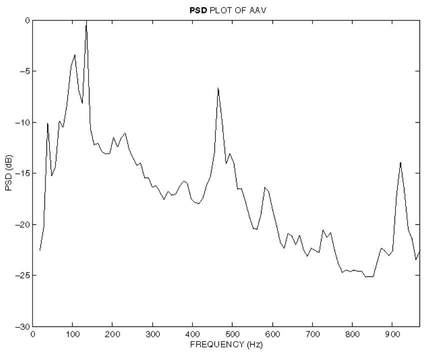
single measurement

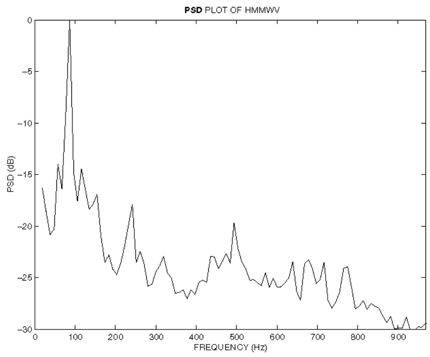
- Complex or absolute value FFT features

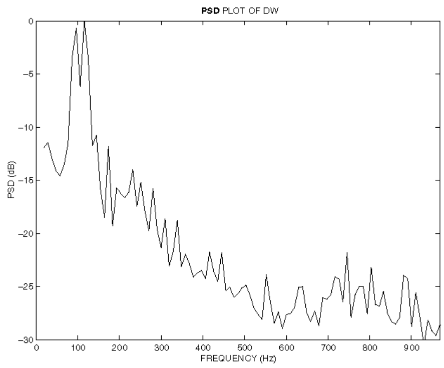
Class Descriptions

- 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)

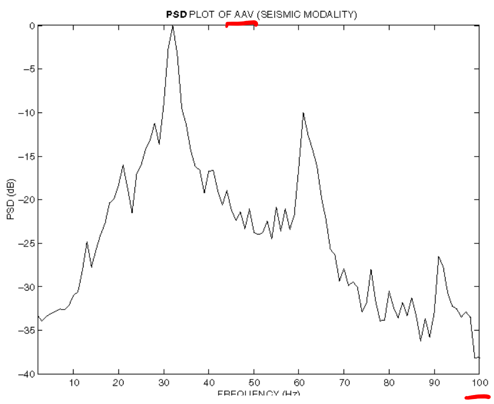
HMV – wheeled
(Humvee)

DW – wheeled
(Dragon Wagon)

SITEX02 Data. DARPA SenseIT Program

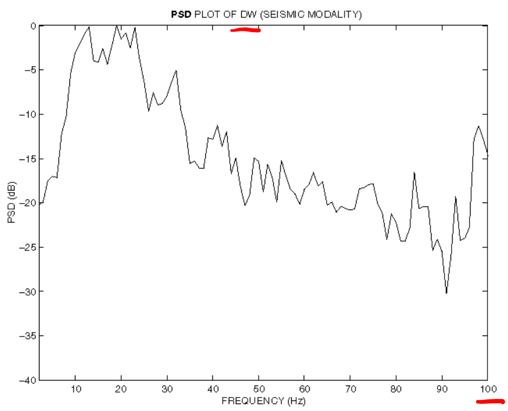
Representative Seismic FFT Features

(a)

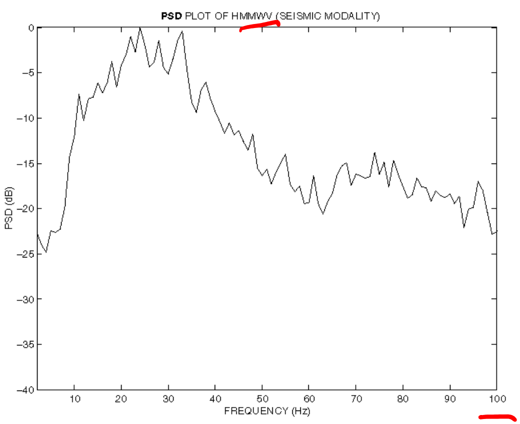


N=50

(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

Absolute-value FFT acoustic features

Gaussian Classifier

classifier

actual

ω_m \ C(**X**)	Wheeled	Tracked	
Wheeled	109 ✓	11 ✗	120
Tracked	22 ✗	98 ✓	120

wheeled tracked

PD = 0.91, 0.82, Ave = 0.86

109/120

PFA = 0.18, 0.09

22/120

NN Classifier (benchmark)

classifier

actual

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

PD = 0.85, 0.99, Ave = 0.92 higher better

PFA = 0.01, 0.15 lower better

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	60
DW	12	42	6	
HMV	15	14	31	

27

120 not AAV

AAV DW HMV

PD = 0.88, 0.70, 0.52, Ave = 0.70

53/60 AAV

PFA = 0.22, 0.16, 0.07

27/120

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

Multiple measurements
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

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 slightly lower

PFA = 0.27, 0.08
lightly higher

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?