

AUDIO SIGNAL PROCESSING FOR SURVEILLANCE APPLICATIONS

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Presented by

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CONTEXT

Group: Grupo de Tratamiento de Señal (Signal Processing Group)

Institution: Institute of Telecommunicacion and Multimedia Applications, Universidad Politécnica de Valencia (Polytechnic University of Valencia), SPAIN.

Members: 11 doctors, 14 undergraduate and postgraduate students/researchers.

Expertise:

Theory:

➢ signal detection and classification, time-frequency, nonlinear signal processing, higher-order statistics, image morphology algorithms, independent component analysis,...

Applications:

>Non-destructive testing of materials: ultrasonic and impact methods

Surveillance systems: video, infrared and audio.

Different applications of video analysis





CONTEXT

✓HESPERIA: Homeland sEcurity: tecnologíaS Para la sEguridad integRal en especios públicos e infrAestructuras. 2006-08. CENIT Programme.

✓ Early warning of forest fires based on infrared signal processing. Special Programme of Valencia Government.



INDEX

✓ Surveillance based on audio signals

- ✓ Statistical signal processing
- ✓ Experiences and demos



Why surveillance based on audio signals?

Sound gets information not accessible from video

Hidden targets
 Surveillance in dark sites
 Abnormal sounds in normal images

✓Sound gets information to be combined with video information

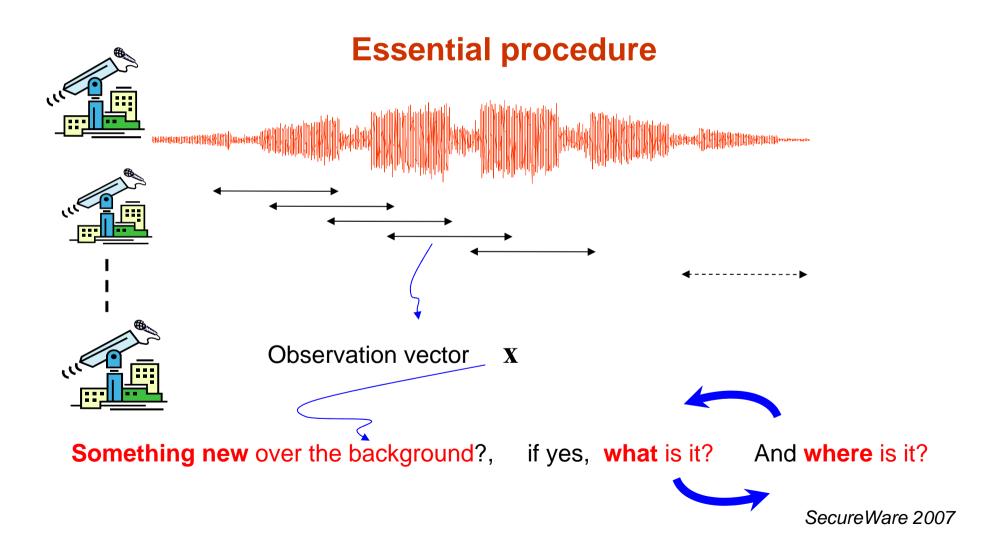
>Improved performance by decision/classification fusion

➤Idex of video stream

Steering of video camera to "interesting" directions

✓ Sounds (except when voices are involved) achieves
 larger degree of privacy in comparison with video Secure Ware 2007







Some examples of sound based surveillance

✓ Surveillance at elevators

Radhakrishnan, R.; Divakaran, A., <u>"Systematic Acquisition of Audio Classes for</u> <u>Elevator Surveillance"</u>, *SPIE Image and Video Communications and Processing*, Vol. 5685, pp. 64-71, March 2005.

■8 sound classes in elevators are learned from 61 clips (1 hour) of suspicious events and 4 clips (40 minutes) without events:

Alarm, banging, elevator background, door opening & closing, elevator bell, footsteps, non-neutral speech, normal speech.

•A two step procedure was implemented: **detection** plus clustering

 Once learned a supervised classifier was designed to clasify every 1 sec of sound.



Some examples of sound based surveillance

✓ Surveillance at home

Istrate et al.: <u>"Remote monitoring sound system for distress situations detection,"</u>, Innovation et technologie en biologie et médecine ,ITBM-RBM, 2006.

- Telesurveillance at home for elderly people and/or chronic patients.
- Different sensors combined with 1 microphone per room.
- Analyis window 32 ms.
- •Detection followed by classification in 7 predefined classes of sounds:

Door closing, glass breaking, telephone sound, footsteps, scream, dishes, locks

Training+verfication based on 3354 files (3 hours)



Some examples of sound based surveillance

✓ Surveillance at office

Härma, M. F. McKinney, J. Skowronek: <u>"Automatic Surveillance of the Acoustic Activity</u> <u>in our Living Environment"</u>, Proc. IEEE International Conference on Multimedia and Expo., Amsterdam, July 2005.

- Continous leraning of interesting sounds in office environment
- Analysis window 62 ms.
- **Detection** followed by **classification** in 25 subjectively selected classes of sounds:
 - Door closing, noise from different devices, voices,...
- 140.000 interesting events were recorded during 2 months

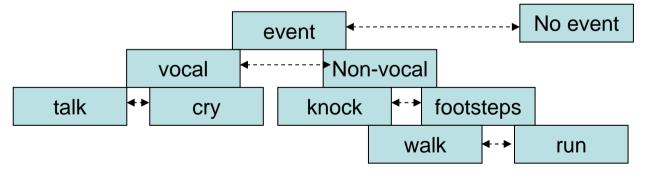


Some examples of sound based surveillance

P. K. Atrey et al.: <u>"Audio Based Event Detection for Multimedia Surveillance"</u>, Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, Toulouse (France), May 2006.

Classification of sounds at office corridor into 6 categories

A hierarchical approach is proposed:



Analysis window 50 ms

• 10 min of each even for training, 2 hours of recording for testing SecureWare 2007



Some examples of sound based surveillance

✓ Surveillance for intruder detection

•E. Menegatti, E. Mumolo, M. Nolich, E. Pagello "<u>A Surveillance System based on</u> <u>Audio and Video Sensory Agents cooperating with a Mobile Robot</u>" Proc. of 8th International Conference on Intelligent Autonomous Systems (IAS-8), March 2004, Amsterdam HOLANDA pp. 335-343

- Audio+vision surveillance of the storage room of a shipping company
- ■6 microphone arrays (4 elements)+1 static omnidirectional camera+1 mobile robot with a camera
- Initial detection is made by the static camera, then the arrays steer towards the intruder and track it from the footsteps sound.
- Information on the location of the intruder is sent to the mobile robot to persue the intruder
 SecureWare 2007



Some examples of sound based surveillance

✓ Surveillance at the city

G. Valenzise et al.: <u>"Scream and Gunshot Detection and Localization for Audio-Surveillance Systems"</u>, Proc. IEEE International Conference on Advanced Video and Signal based Surveillanace, London, September 2007.

•A *classifier* is implemented to distinguish gunshots from background noise or scream from background noise

• Then the sound source is **localized** by array processing and a camera is steered towards it.

Analyis window 23 ms.

Training+verfication based on movie records, internet clips and recordings from a public square at Milan



Some examples of sound based surveillance

C. Clavel et al.: <u>"Events detection for an audio-based surveillance system"</u>, Proc. IEEE International Conference on Multimedia and Expo., Amsterdam, July 2005

- Performs shot detection versus normality
- Analyis window 20 ms, but a final decision is made every 0.5 sec.
- Background has been recorded in public spaces, then shots from a CD of radio recordings have been added
- Training+verfication besed on 134 shots (296 s) and 797 segments of normal noise of public places



Some examples of sound based surveillance

✓ Surveillance at railway stations

W. Zajdel et al.: <u>"CASSANDRA: Audio-video Sensor Fusion for Aggression</u> <u>Detection"</u>, Proc. IEEE International Conference on Advanced Video and Signal based Surveillanace, London, September 2007.

Analysis of voices in aggression condition, oriented to railway stations

• Fusion between audio and video is made from a probabilistic model and bayesian inference

Presence of noise of trains is detected from video information to avoid false alarms

I3 clips (100 to 150 sec.) with actors in a railway station were recorded to test the system
Secure 4



Some conclusions from the examples

✓There is a variety of scenarios and objectives

✓The analysis window length is somewhat arbitrary

✓Novelty detection is a key aspect in all cases

 We may require non-supervised (learning the environment by clustering) and supervised (predefined classes of sounds)
 classification

✓Localization is sometimes required



What main difficulties do we have?

Complex and variant background producing high intensity sounds which should not confuse the sound surveillance system

✓How we design/train the system to satisfy some quality requirements?



What help do we need?

✓ Statistical signal processing allows the design of algorithms satisfying optimization criteria in a large variety of statistical models of the involved signals

Control of probability of false alarm while maximizing probability of detection

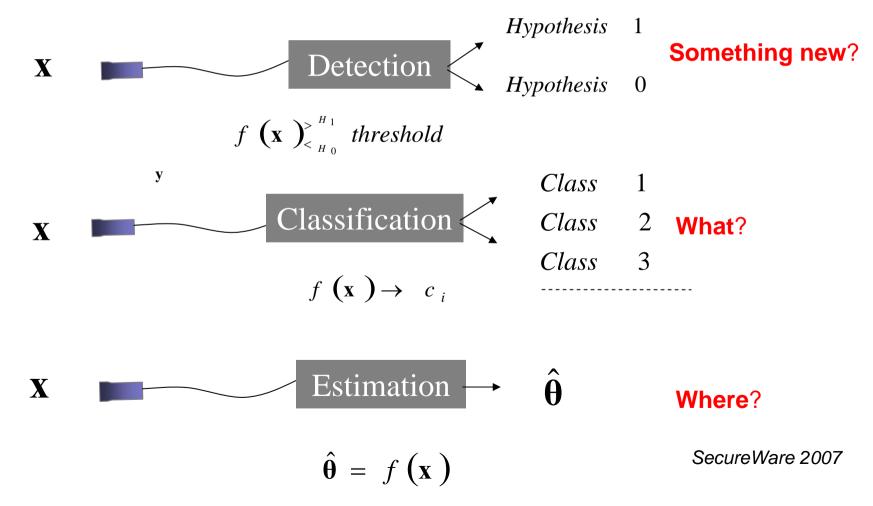
Selection of the most probable kind of sound

Minimization of location/tracking errors



STATISTICAL SIGNAL PROCESSING

Given observation vector **x**, what is the optimum processing function $f(\mathbf{x})$?





STATISTICAL SIGNAL PROCESSING Optimum detector: general

$$f(\mathbf{x}) = \frac{P(\mathbf{x} / H_1)}{P(\mathbf{x} / H_0)} \stackrel{>^{H_1}}{\underset{<_{H_0}}{}} threshold = \lambda$$

 $P(\mathbf{x}/H_i)$ Is the probability density function (PDF) of **y** conditioned to H_i is the true hypothesis

 $f(\mathbf{x})$ Is called the likelihood ratio

 λ Is selected to fit a probability of false alarm (*PFA*) then probability of detection (*PD*) is maximized

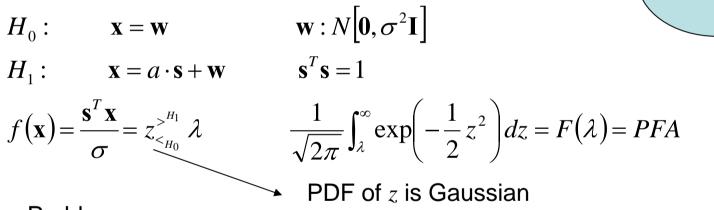
Something new over the background?,

if yes, what is it? And where is it?



Matched filter

STATISTICAL SIGNAL PROCESSING Optimum detector: known signal in white Gaussian noise background



Problems:

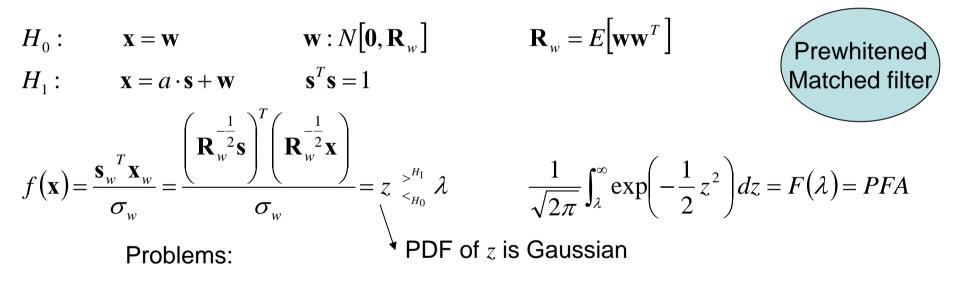
Noise must be white Gaussian

>Adaptive estimation of **noise level** σ is necessary

>A priori knowledge of s is required



STATISTICAL SIGNAL PROCESSING Optimum detector: known signal in coloured Gaussian noise background

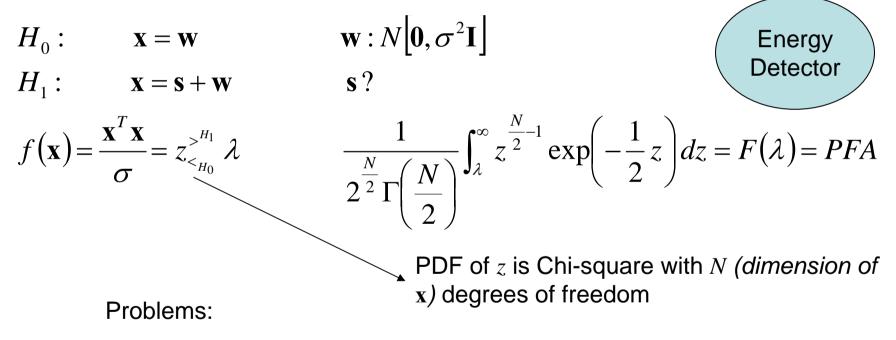


Noise must be coloured Gaussian

Adaptive estimation of noise autocorrelation matrix R_w is necessary
 A priori knowledge of s is required



STATISTICAL SIGNAL PROCESSING Optimum detector: unknown signal in white Gaussian noise background

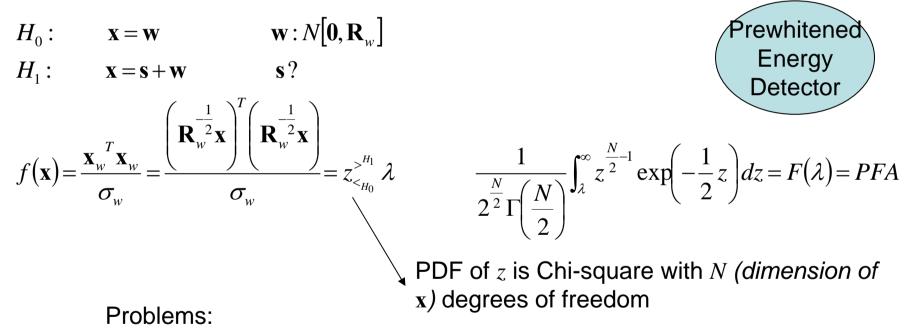


>Noise must be white Gaussian

>Adaptive estimation of **noise level** σ is required



STATISTICAL SIGNAL PROCESSING Optimum detector: unknown signal in coloured Gaussian noise background

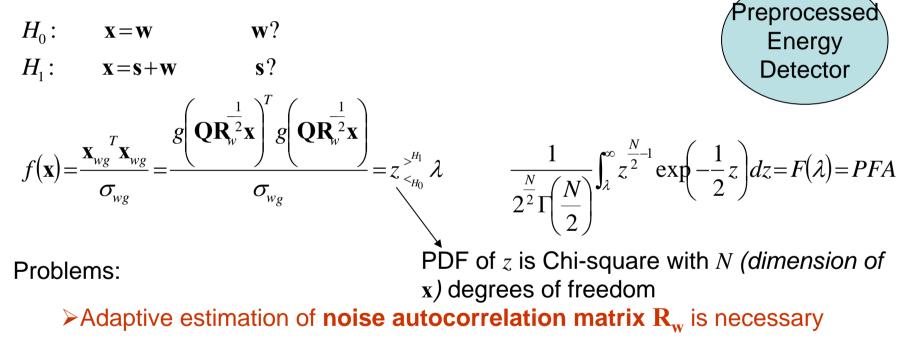


>Noise must be **coloured Gaussian**

>Adaptive estimation of **noise autocorrelation matrix** \mathbf{R}_{w} is necessary



STATISTICAL SIGNAL PROCESSING Optimum detector: unknown signal in coloured nonGaussian noise background



>Adaptive estimation of rotation matrix \mathbf{Q} and nonlinear mapping g(.) is necessary

>Adaptive estimation of (transformed) noise level σ_{wg} is necessary. SecureWare 2007



STATISTICAL SIGNAL PROCESSING Optimum detector: learning the parameters off-line

We have a training set of background noise observation vectors:

$$\begin{split} \mathbf{w}_{l} & l = 1....L \\ \hat{\sigma}^{2} = \frac{1}{N \cdot L} \sum_{l=1}^{L} \mathbf{w}_{l}^{T} \mathbf{w}_{l} \\ \hat{\mathbf{R}}_{w} = \frac{1}{L} \sum_{l=1}^{L} \mathbf{w}_{l} \mathbf{w}_{l}^{T} \\ \hat{\mathbf{g}} & \\ \hat{\mathbf{Q}} & \end{pmatrix} \quad \hat{\mathbf{Q}} = \frac{1}{L} \sum_{l=1}^{L} \hat{g} \left(\hat{\mathbf{Q}} \hat{\mathbf{R}}_{w}^{-\frac{1}{2}} \mathbf{w}_{l} \right) \mathbf{w}_{l}^{T} \hat{\mathbf{R}}_{w}^{-\frac{1}{2}} \longrightarrow \\ \hat{\sigma}_{wg}^{2} = \frac{1}{N \cdot L} \sum_{l=1}^{L} g \left(\mathbf{Q} \mathbf{R}_{w}^{-\frac{1}{2}} \mathbf{w}_{l} \right)^{T} g \left(\mathbf{Q} \mathbf{R}_{w}^{-\frac{1}{2}} \mathbf{w}_{l} \right) \end{split}$$
Nonlinear equations, can be solved by iterative methods



STATISTICAL SIGNAL PROCESSING Optimum detector: learning the parameters on-line

We update the parameters with every new observation vector where H_0 has been selected

$$\hat{\sigma}_{t+1}^{2} = \alpha \hat{\sigma}_{t}^{2} + (1 - \alpha) \mathbf{w}_{t}^{T} \mathbf{w}_{t}$$

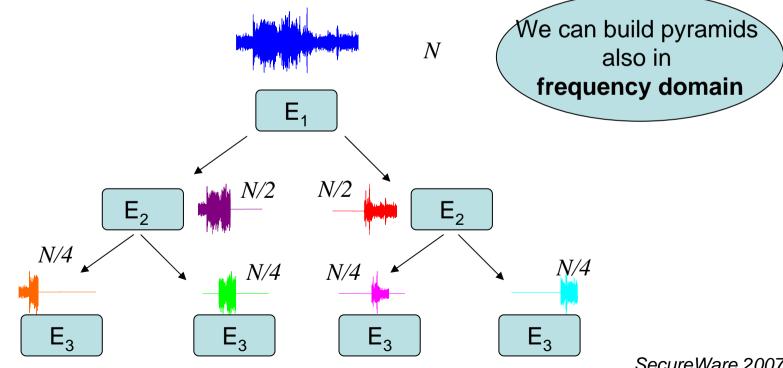
$$\hat{\mathbf{R}}_{w(t+1)} = \beta \hat{\mathbf{R}}_{w(t)} + (1 - \beta) \mathbf{w}_{n} \mathbf{w}_{n}^{T}$$

$$\hat{g}_{\mathbf{\hat{Q}}} \rightarrow \hat{\mathbf{Q}}_{t+1} = \frac{1}{M} \sum_{l=t-M}^{t} \hat{g}_{t+1} \left(\hat{\mathbf{Q}}_{t+1} \hat{\mathbf{R}}_{wt}^{-\frac{1}{2}} \mathbf{w}_{l} \right) \mathbf{w}_{l}^{T} \hat{\mathbf{R}}_{wt}^{-\frac{1}{2}} \longrightarrow \begin{array}{l} \text{Nonlinear equations, can be solved by iterative methods} \\ \hat{\sigma}_{wg(t+1)}^{2} = \varepsilon \hat{\sigma}_{wg(t)}^{2} + (1 - \varepsilon) g \left(\hat{\mathbf{Q}}_{t} \hat{\mathbf{R}}_{w(t)}^{-\frac{1}{2}} \mathbf{w}_{t} \right)^{T} g \left(\hat{\mathbf{Q}}_{t} \hat{\mathbf{R}}_{w(t)}^{-\frac{1}{2}} \mathbf{w}_{t} \right)$$



STATISTICAL SIGNAL PROCESSING **Optimum detector: dealing with unknown duration** of the event

We can try different values of dimension N to improve detectability:

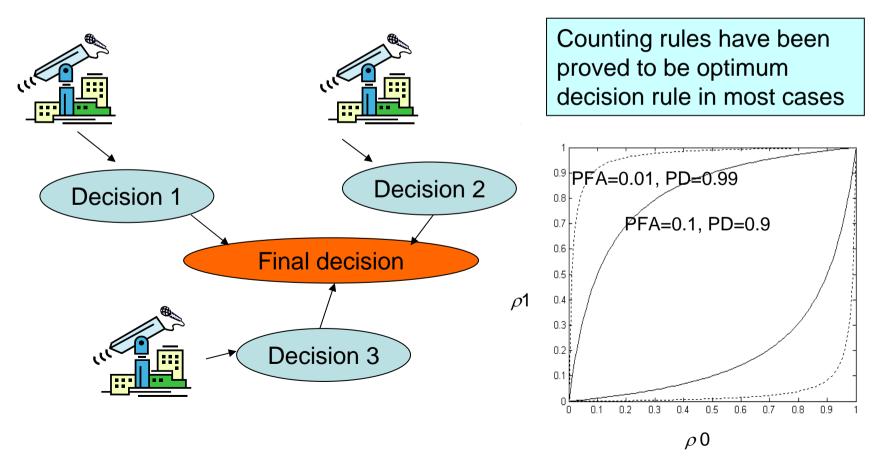


A pyramid of energy detectors



STATISTICAL SIGNAL PROCESSING Optimum detector: dealing with fusion of decisions from different microphones

We can try different values of dimension N to improve detectability:





STATISTICAL SIGNAL PROCESSING

Optimum detector: summary

✓ Energy detector overcomes the unknowledge about signal waveform

 ✓ Prewhitening-rotation-nonlinear mapping are required in the most general case before computing the energy

✓ Fitting the threshold for a required PFA is an easy problem

Learning the background (i.e., training the detector) is a complex problem which should be very specific for every scenario/applicatio

- ✓ Frequency domain can be very useful in some cases
- ✓ **Decision fusion** is not complicated in general



STATISTICAL SIGNAL PROCESSING Optimum classifier: why classify?

✓Once a detection is made, determining the kind of sound may be useful to:

>Determine the degree of threat of the event

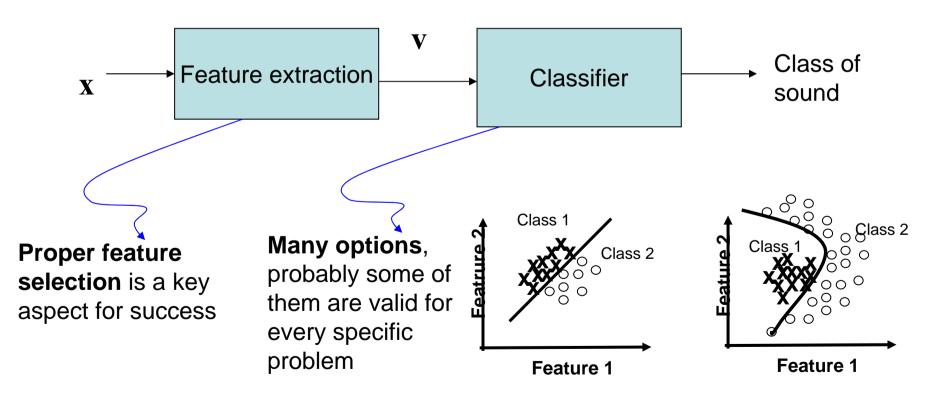
>Help in establishing the best strategy against the threat





STATISTICAL SIGNAL PROCESSING

Optimum classifier: basic scheme





STATISTICAL SIGNAL PROCESSING Optimum classifier: general

✓The classifier should select the most probable class given the observed feature vector, then the key problem is to determine

$$p(C_k / \mathbf{v})$$
 Then we select C_k having $\max_{C_{k'}} p(C_{k'} / \mathbf{v})$

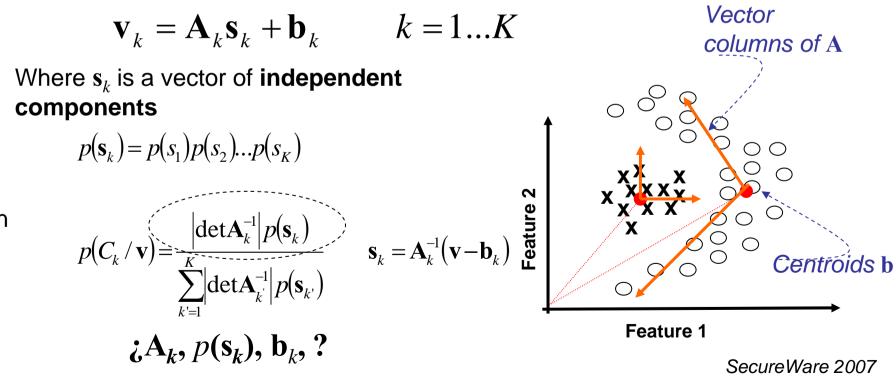
 $p(C_k / \mathbf{v}) = \frac{p(\mathbf{v} / C_k) \cdot P(C_k)}{p(\mathbf{v})}$ We have a problem of multivariate PDF estimation

Using Bayes



STATISTICAL SIGNAL PROCESSING Optimum classifier: a general model

Let us assume that the feacture vectors of class C_k can be expresses as



then



STATISTICAL SIGNAL PROCESSING Optimum classifier: Gaussian case

White case
$$\mathbf{v}_k = \mathbf{s}_k + \mathbf{b}_k$$
 $k = 1...K$
 $p(C_k / \mathbf{v}) \propto \|\mathbf{v} - \mathbf{b}_k\|^2 = (\mathbf{v} - \mathbf{b}_k)^T (\mathbf{v} - \mathbf{b}_k)^T$

Coloured case
$$\mathbf{v}_k = \mathbf{R}_k^{\frac{1}{2}} \mathbf{s}_k + \mathbf{b}_k$$
 $k = 1...K$

$$p(C_k / \mathbf{v}) \propto \left\| \mathbf{R}_k^{-\frac{1}{2}} (\mathbf{v} - \mathbf{b}_k) \right\|^2 = (\mathbf{v} - \mathbf{b}_k)^T \mathbf{R}_k^{-1} (\mathbf{v} - \mathbf{b}_k)$$



STATISTICAL SIGNAL PROCESSING Optimum classifier: Training (supervised)

$$\mathbf{v}_{k}^{(l)} \qquad l = 1...L_{k}, \qquad k = 1...K$$

$$\hat{\mathbf{b}}_{k} = \frac{1}{L_{k}} \sum_{l=1}^{L_{k}} \mathbf{v}_{k}^{(l)}$$

$$\hat{\mathbf{R}}_{k} = \frac{1}{L_{k}} \sum_{l=1}^{L_{k}} \left(\mathbf{v}_{k}^{(l)} - \hat{\mathbf{b}}_{k} \right) \left(\mathbf{v}_{k}^{(l)} - \hat{\mathbf{b}}_{k} \right)^{T}$$

$$\mathbf{A}_{k}$$

$$p(\mathbf{s}_{k})$$
In the general nonGaussian case we can use Independent Component Analysis iterative algorithms to estimate the mixing matrix

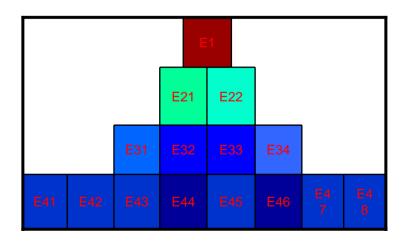


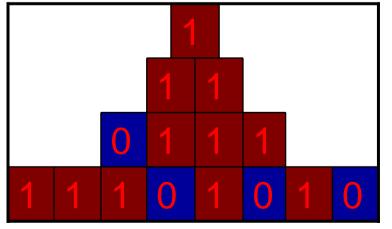
STATISTICAL SIGNAL PROCESSING

Optimum classifier: what about features ?

✓There is some trend to use features which are usual in speech analysis: cepstral parameters. There could be not appropriate for general kind of sounds.

✓Why not trying energy features coming from the pyramid analysis?





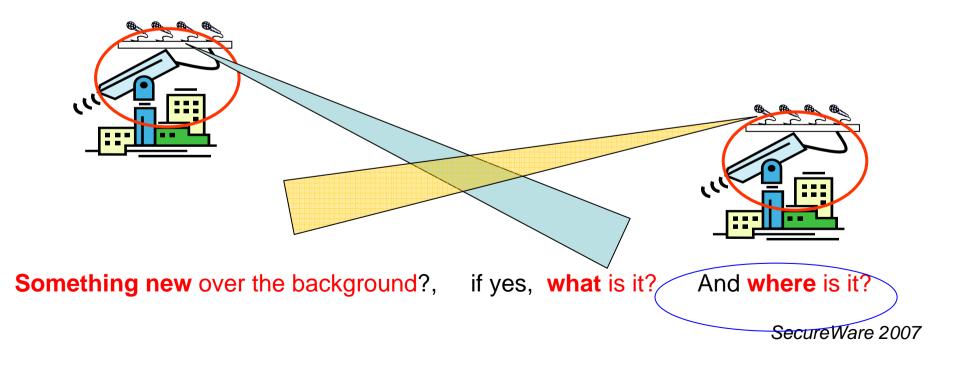


STATISTICAL SIGNAL PROCESSING

Optimum location: basics

✓We need an array of microphones instead of only one microphone

✓By triangularization we can locate the source of sound





STATISTICAL SIGNAL PROCESSING Optimum location: DOA estimation I

✓ Every array must estimate the direction of arrival of the sound source

 \checkmark This is a classical estimation problem

✓The optimum estimator should maximize the probability of the observation vector conditioned to the angle of arrival

$$P(\mathbf{x} / \gamma)$$

✓ Solutions are well-known in the **Gaussian noise case**



STATISTICAL SIGNAL PROCESSING Optimum location: DOA estimation I

$$\mathbf{x}_{l} = \begin{bmatrix} x_{l1} \dots x_{lM} \end{bmatrix}^{T} \qquad i = 1 \dots L$$

Snapshots formed by the values received at the same time in every sensor

$$\hat{\gamma} = \max_{\gamma} \left[\mathbf{a}(\gamma)^T \, \hat{\mathbf{R}} \, \mathbf{a}(\gamma) \right] \rightarrow \underbrace{\begin{array}{l} \text{Spacial energy} \\ \text{detector} \end{array}}_{\substack{\gamma}} \\ \mathbf{a} = \left[1 e^{-j2\pi \frac{d}{c} fsen \gamma} \dots e^{-j2\pi \frac{dM}{c} fsen \gamma} \right]^T \qquad \underset{\substack{\mathsf{B} \\ \mathsf{B} \\$$

Narrowband case. The sanpshots are assumed to be composed by a spatial sinusoid in spatial white Gaussian noise



STATISTICAL SIGNAL PROCESSING Optimum location: DOA estimation II

$$\mathbf{x}_{l}(f_{i}) = [x_{l1}(f_{i})...x_{lM}(f_{i})]^{T}$$
 $i = 1...L$

$$\hat{\gamma} = \frac{1}{I} \sum_{i=1}^{I} \max_{\gamma} \left[\mathbf{a}_{f_i} (\gamma)^T \hat{\mathbf{R}}_{f_i} \mathbf{a}_{f_i} (\gamma) \right]$$
$$\mathbf{a}_{f_i} (\gamma) = \left[1 \ e^{-j2\pi \frac{d}{c} f_i sen\gamma} \dots e^{-j2\pi \frac{dM}{c} f_i sen\gamma} \right]^T$$
$$\hat{\mathbf{R}}_{f_i} = \frac{1}{L} \sum_{l=1}^{L} \mathbf{x}_l (f_i) \mathbf{x}_l^T (f_i)$$

Snapshots formed by the values of the Fourier transform of the received signals in every sensor

Wideband case. For every frequency, the sanpshots are assumed to be composed by a spatial sinusoid in spatial white Gaussian noise