

NSF Workshop on  
Distributed Communications and Signal Processing  
Chicago, Dec 3-4 2002

**Distributed Signal Processing  
and Communications:  
On the Interaction of Source  
and Channel Coding**

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**Outline**

- 1. The view of the world: many to many!**
- 2. Wireless sensor networks**
  - trade-offs in precision, computation, communication, power, delay
- 3. Interesting data sets and their structure**
  - plenoptic and plenacoustic functions
- 4. Correlated source coding**
  - Slepian-Wolf, Wyner-Ziv and distributed KLT
- 5. Uncoded transmission**
  - simple yet powerful
- 6. Sensor networks and source-channel coding**
  - to separate or not to separate
- 7. Conclusions**

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## Acknowledgements

- Swiss and US NSF
- The National Competence Center on Research  
“Mobile Information and Communication Systems”
- K.Ramchandran and his group at UC Berkeley
- M.Gastpar (EPFL-Berkeley)
- P.L.Dragotti (EPFL-Imperial College)
- T.Ajdler, R.Cristescu and G.Barrenechea (EPFL)
- the reading group on DSPC

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## The Swiss National Competence Center on Research “Mobile Information and Communication Systems” <http://nccr-mics.ch>

**Goal:** study fundamental and applied questions raised by new generation mobile communication and information services, based on self-organisation.

**Cross-layer investigation:** mathematical issues (statistical physics based analysis, information and communication theory) to networking, signal processing, security, distributed systems, software architecture and economics.

**Examples:** ad-hoc and sensor networks, peer-to-peer systems

**Network of researchers:**

- EPFL, ETHZ, CSEM, UNI-BE,L,SG,ZH
- 30 professors, 70 PhD students
- 11 individual projects

**Budget:**

- 8 MSfr/Year (5.3 M\$/Y)
- 4-10 years horizon

**Note:** similar to a US ERC or STC

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## 1. The view of the world: many to many!

### Signals exist everywhere...they just need to be sensed!

- distributed signal acquisition
- one can put many cameras, microphones etc
- these signals are not independent
  - the more sensors, the more correlation
- there can be some substantial structure

### Computation is cheap

- local computation
- complex algorithms to retrieve data are possible

### Communication is everywhere

- mobile ad hoc networks are studied
- dense, self-organized sensor networks are built
- the cost of mobile communications is still the main constraint

**This creates a new challenging set of signal processing and communications problems**

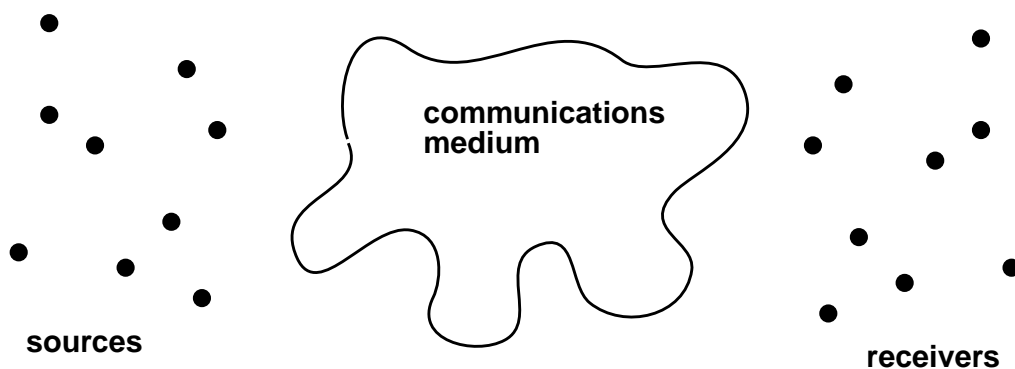
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## The Change of Paradigm

**Old view: one source, one channel, one receiver**



**New view: distributed sources, many sensors/sources, distributed communication medium, many receivers**



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## **Individual Project #7 (IP7) of NCCR-MICS** <http://ip7.mics.ch/>

**This project is concerned with the change of paradigm induced by large distributed sensing and communications.**

**This leads to questions on**

- distributed signal acquisition and sampling,
- representation of dependent data (eg plenoptic/plenacoustic fct),
- distributed compression of correlated data,
- transmission and joint source-channel coding,
- reconstruction of distributed signals.

**Applications can be found in**

- sensor network (sensing and transmission of physical phenomena),
- ad-hoc networks (real-time services) and
- monitoring (multi-camera systems)
- virtual reality systems (synthesis)

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## **2. Wireless sensor networks**

**Trade-offs between**

- acquisition accuracy
- computational power
- transmission power
- delay
- accuracy etc

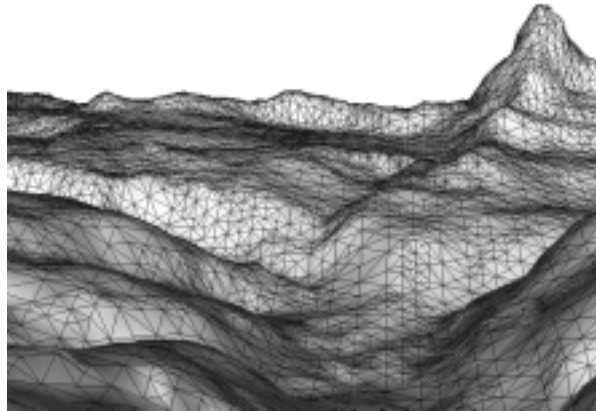
**Characteristics**

- very low power
- fixed but unknown location
- constrained traffic pattern

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## The swiss version of homeland security ;)

**Distributed sensor network for avalanche monitoring:**



**Method: drop sensors, self-organized triangulation, monitoring of location/distance changes, download when critical situation**

**Challenges: extreme low power, high precision, asleep most of the time, when waking up, quick download**

**all self-organized!**

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## 3. Interesting data sets and their structure

### 3.1 The Plenoptic Function [Adelson, Shum etc]

#### Multiple camera systems

- distributed signal acquisition
- multiple cameras

#### Plenoptic sampling

- physical world (e.g. landscape, room)
- one can put many cameras
- how many are required to reconstruct a view from any point
- this is a sampling and interpolation problem

#### Background:

- pinhole camera & epipolar geometry
- multidimensional sampling

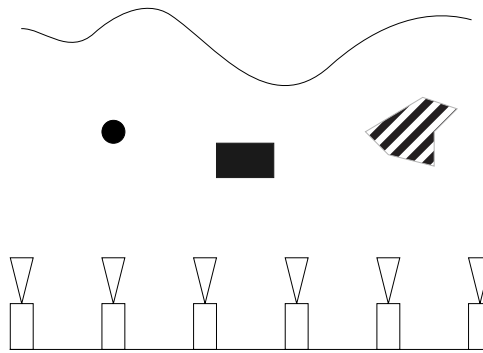
#### Implications on communications

- camera sources are correlated in a particular way
- limits on number on "independent" cameras
- different BW requirements at different locations

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## On Plenoptic Sampling

### Model



### Questions:

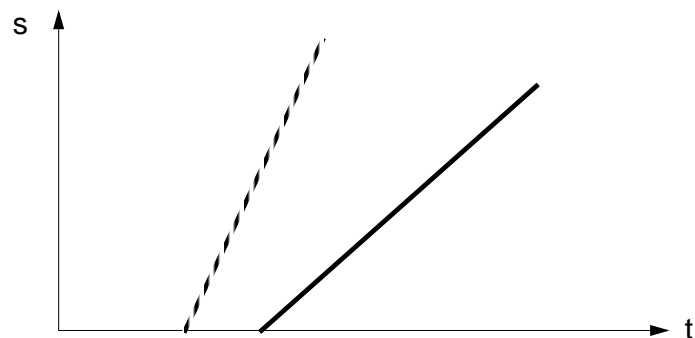
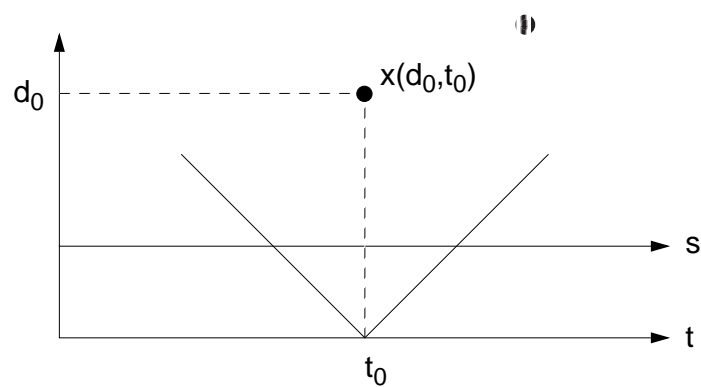
- how many pictures are “enough” to interpolate any view?
- how to interpolate between the cameras

### Plenoptic function

- is it bandlimited? (no...)
- how to approximate it
- implications on correlated source coding

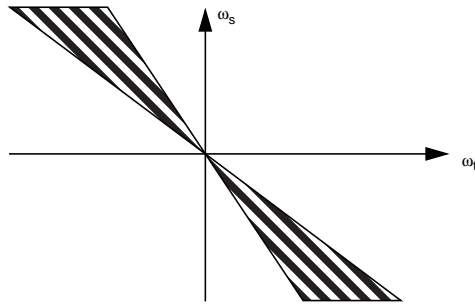
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## The Plenoptic Function



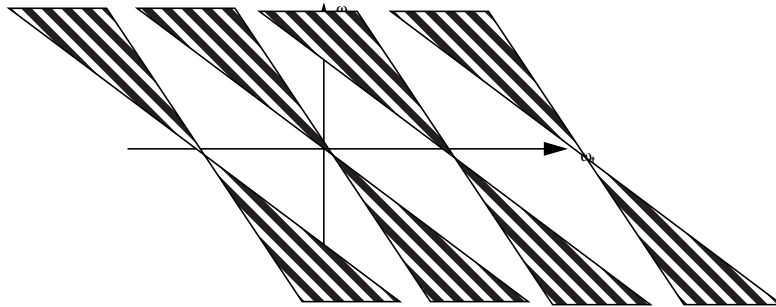
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**Fourier transform:**



angle depends on depth of field.

**Sampling [Shum et al]:**



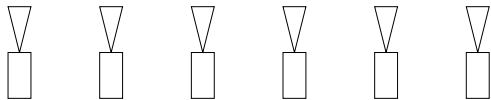
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## Examples of recent results

### 1. Bandlimited walls/fcts

[DoMMV:02] Plenoptic function  
not BL unless linear wall.

**Proof: FM modulation!  
Bessel functions**



### 2. Plenoptic function of finite complexity objects

[Maravic et al] For certain "simple scenes" (collection of Diracs),  
the plenoptic function can be sampled with

- finite number of cameras
- finite number of samples

**and reconstructed perfectly.**

**Proof: Radon transform + sampling of FRI signals**

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### 3.2 The plenacoustic function [AjdlerV:02]

#### Multiple microphones

- distributed signal acquisition of sound
- multiple microphones

#### Sound plenacoustic sampling

- physical world (e.g. landscape, room)
- one can put many microphones
- how many are required to reconstruct a spatial sound at any point (or between them)
- this is a sampling and interpolation problem

#### Implications on communications

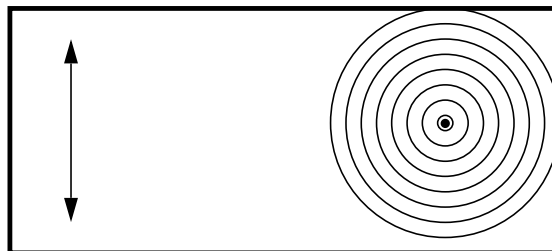
- sound sources are correlated in a particular way
- limits on number on "independent" microphones
- different BW requirements at different locations

**Note: also holds for range data, and other wave equation related data**

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### Plenacoustic function and its sampling

**Set up:**



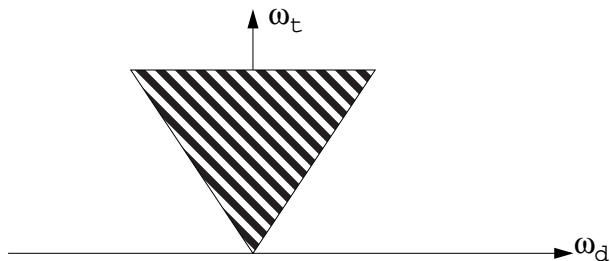
**Can we sample with "few" microphones and hear any location?**

**In this simple case, one could solve the wave equation, but in general, it is much simpler to sample the plenacoustic fct**

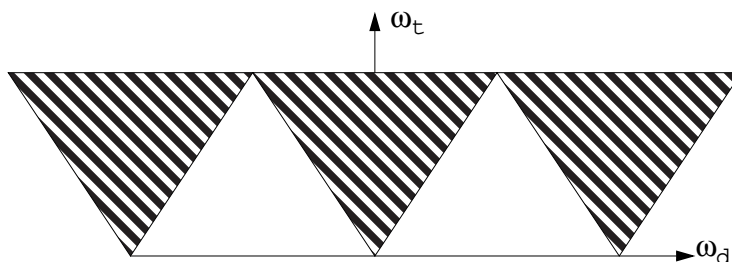
**Dual question also of interest**

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**Plenacoustic function in Fourier domain:**

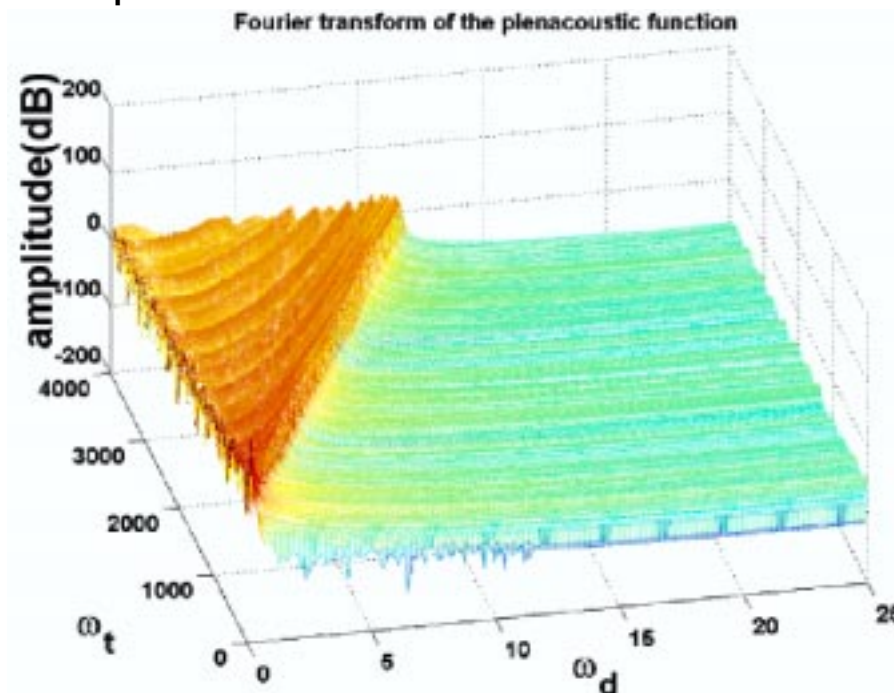


**Sampled version:**



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**Example of a plenacoustic function**



**nice and bandlimited!**

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## 4. Correlated source coding and transmission

### Dense source = correlated sources

- physical world (e.g. landscape, room)
- degrees of freedom "limited"
- denser sampling: more correlated sources

### Background:

- Slepian- Wolf (lossless correlated source coding with binning)
- Wyner-Ziv (source coding with side information)
- Note that lossy Wyner-Ziv is still an open problem...

### Implications on communications

- such results are rarely used...
- many open problems
- many tough problems in the usual set up

are there limiting results?

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## Slepian-Wolf 1973

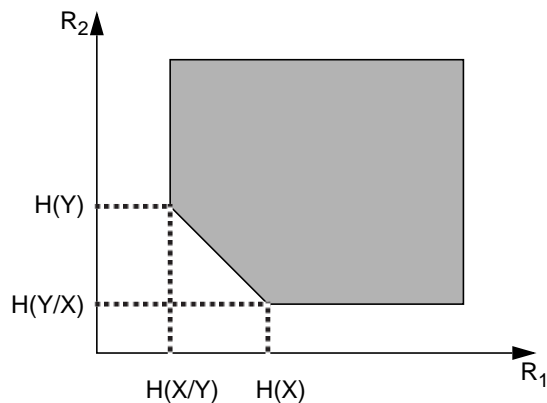
### Given

- $X, Y$  i.i.d with  $p(x,y)$

Then: code separately, decode jointly

### Achievable rate region

- $R_1 \geq H(X/Y)$
- $R_2 \geq H(Y/X)$
- $R_1 + R_2 \geq H(X, Y)$



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## Power efficient gathering of correlated data [CristescuV:02]

**Assume: correlated data**

**Goal: find a data gathering tree that minimizes cost**

**Model: (simplification)**

- if you have data alone:  $B$  bits need to be transmitted
- if you have already some other data:  $\beta < B$  bits

**If  $\beta = B$ , simply shortest path tree, easy**

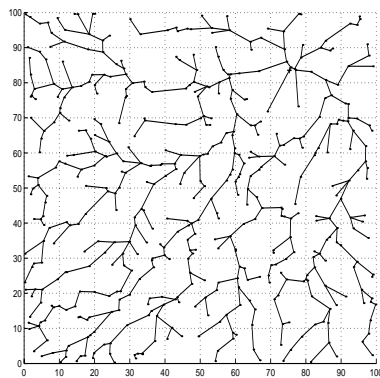
**If  $\beta = 0$ , (multiple) traveling salesman...hard**

**Results [CristescuV:02]**

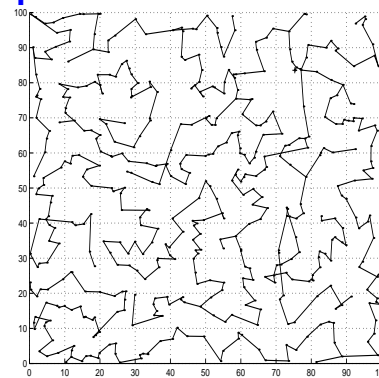
- Problem is in NP
- Good distributed heuristics
- can make a large difference in power consumption

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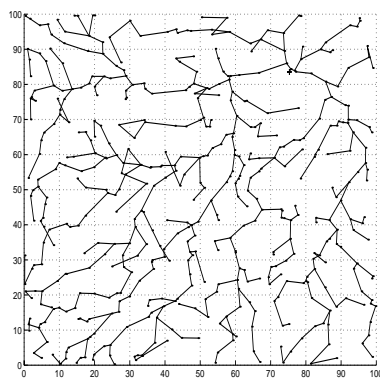
### Example:



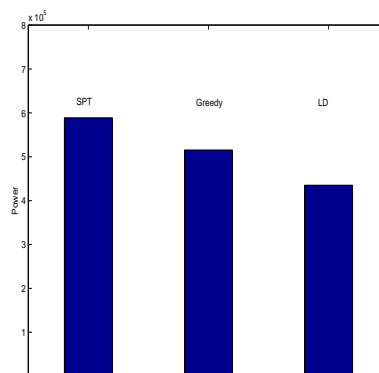
(a) SPT



(b) Greedy algorithm



(c) Leaves deletion heuristic

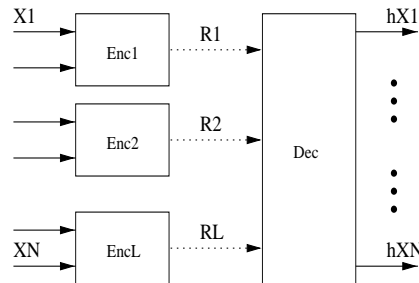


(d) Power efficiency

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## The Distributed Karhunen-Loeve Transform [GastparDV:02]

Assume a correlated vector source  
joint statistics (in particular second order) are known.:



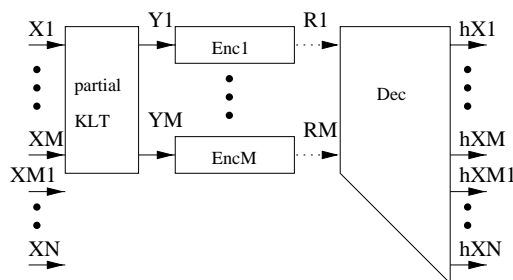
What is the best way to separately compress this source  
by L local compressors, for a joint decoder?

This answers (in part) a distributed source coding problem

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## The partial KLT

Assume only a part of the sources are observed, but the entire  
vector needs to be reconstructed.



**Model:**  $X_{u0} = A X_o + V$  (e.g. jointly gaussian)

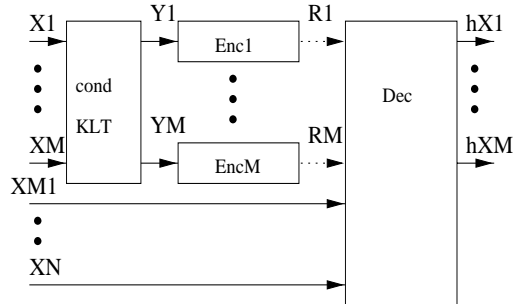
**Results:**

- NLA: k dim. approx. with largest modified eigenvalues
- Compression:  $R(D)$  similar to gaussian, with modified e.vals

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## The conditional KLT

Assume that a part of the sources are available as side information, the others are observed and coded.  
The entire vector needs to be reconstructed.



**Cond. KLT:**  $C \Sigma_{s/\bar{s}} C^T = \text{diag}(\lambda_i)$ , that is, Y cond. uncorrelated

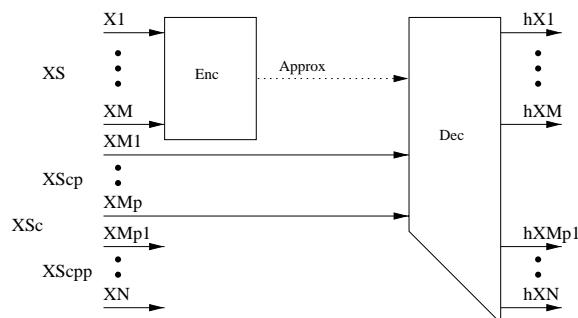
**Results:**

- NLA: k dim. approx = k cond. e.vectors with largest e.value
- Compression: (Gaussian case) separate WZ compression after C

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## The combination

Assume that some sources are available as side information, some sources are observed and coded, and some are hidden.  
The entire vector needs to be reconstructed.



**Result:**

- NLA: use conditional and partial KLT in turn
- Compression: improves non-distributed solution

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## 5. Uncoded transmission and relays networks [GastparRV:02]

It is well known that a Gaussian source over a AWGN channel can be "sent as is", achieving optimal performance

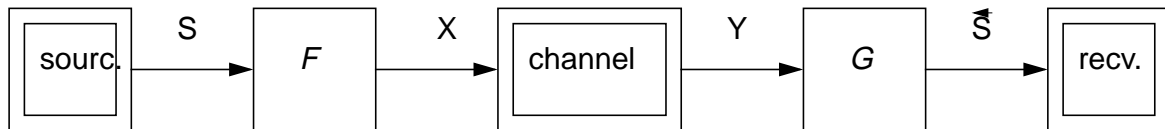
- easy way to achieve best performance

The parameters of source-channel coding are:

- source distribution:  $P_S(s)$
- source distortion or error measure:  $D(s, \bar{s})$
- channel conditional distribution:  $P_{Y/X}(y/x)$
- channel input cost function:  $\rho(x)$

The art is measure matching!

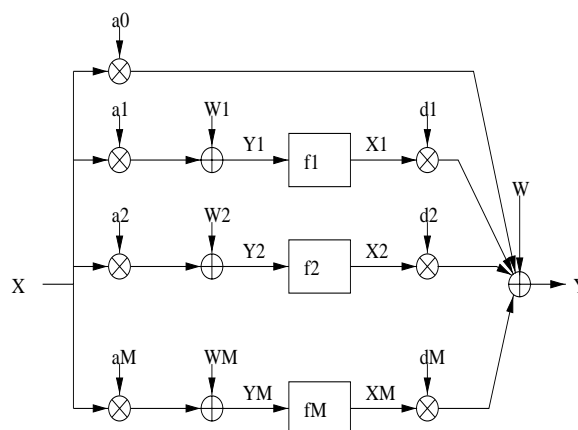
- channel has to look like the test channel to the source
- source has to look like a capacity achieving distrib to the channel



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## Relay network [GastparV:02]

Old and partly open problem from IT



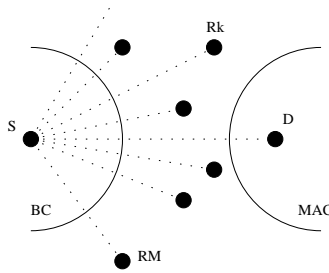
Simple model

Interesting question if number of relays grows...

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## A capacity result for the relay network

**Bound on performance: cut sets for broadcast and MAC**



**Results:**

- under certain technical conditions, capacity of the gaussian relay network as M grows is

$$C = \log( 1 + P/N * \alpha )$$

e.g. if each relay has power Q,  $C \sim \log(1+ MQ/N)$

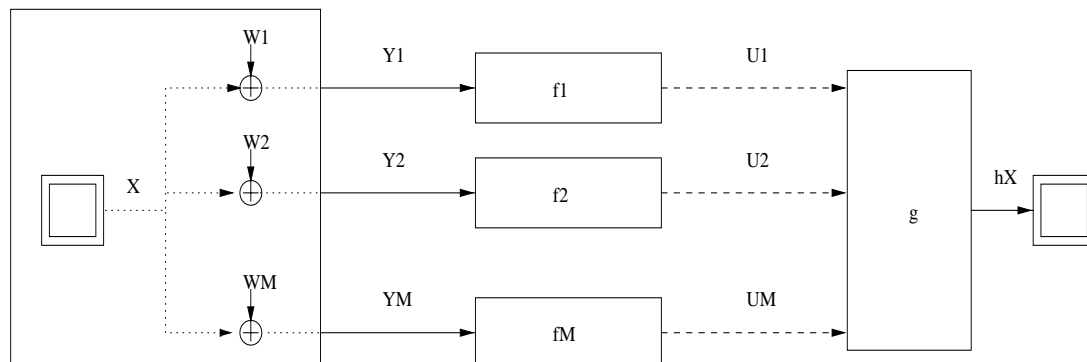
- this is different (and better) from other approaches
- method uses uncoded transmission

## 6. Sensor networks and source-channel coding [GastparV:02]

**Consider the problem of sensing**

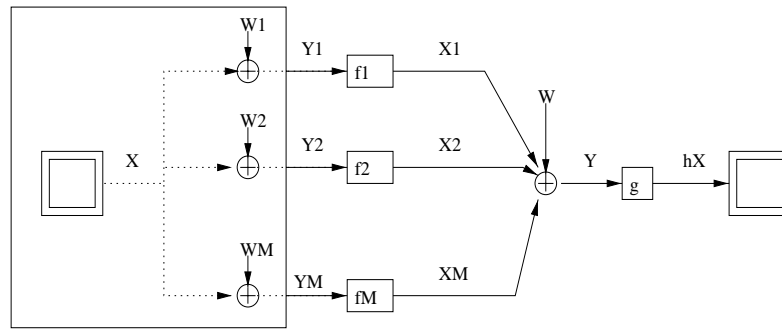
- one source
- many sensors
- reconstruct an estimate

**Model: The CEO problem [Berger et al]**



**Question:** distributed source compression and multiantenna or uncoded transmission?

**Example:**



**Performance:**

- $1/M$  with uncoded transmission
- $1/\log(M)$  with separation

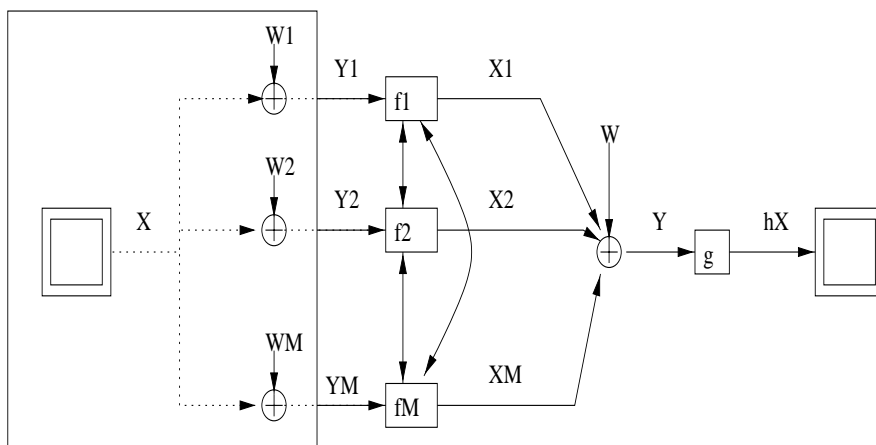
**Can be shown to be optimum performance**

**Condition for optimality: measure matching!**

- $d(s, \bar{s}) = -\log p(s/\bar{s})$ ,
- $I(S, \bar{S}) = I(S; U_1, U_2, \dots, U_N)$

**Can be generalized to many sources  $S_1, S_2, \dots, S_N$**

**It is the best one can do!**



**Communication between sensors does not help as  $M$  grows**

## 7. Conclusions

**There are some good questions in the interaction of**

- sensing
- representation
- compression
- transmission
- decoding

**This goes beyond joint source-channel coding**

- acquisition of the source comes into play
- communications infrastructure influences the sensing
- are there some fundamental bounds on certain data sets?
- are there practical schemes to approach the bounds?

**Many interesting and open problems**

**DSP: Distributed Signal Processing!**

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## References

- M. Vetterli, P. Marziliano, T. Blu. Sampling signals with finite rate of innovation. IEEE Transactions on Signal Processing , vol. 50, no. 6, Jun. 2002, pp. 1417-1428.
- I. Maravic, M. Vetterli, "A Sampling Theorem for the Radon Transform of Finite Complexity Objects", in Proc. ICASSP, May 2002.
- T. Ajdler and M. Vetterli, The plenacoustic function, sampling and reconstruction, IEEE ICASSP-03, submitted.
- R.Cristescu and M.Vetterli, Power efficient gathering of correlated data: Optimization, NP-completeness and heuristics, submitted, Mobihoc 03.
- M. Gastpar, P. L. Dragotti, and M. Vetterli. The distributed Karhunen-Loeve transform. Proc 2002 IEEE International Workshop on Multimedia Signal Processing, December 2002.
- M. Gastpar, B. Rimoldi, M. Vetterli. To code or not to code: lossy source-channel communication revisited, IEEE Transactions on Information Theory, accepted.
- M. Gastpar and M. Vetterli. On the capacity of wireless networks: The relay case. In Proc IEEE Infocom 2002, New York, June 2002.
- M. Gastpar and M. Vetterli. Source-channel communication in sensor networks, submitted, Sensor networks workshop, 2003.

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