NSF Workshop on Distributed Communications and Signal Processing
NCCR MICS Annual Workshop 2003

Distributed Signal Processing and Communications: Acquisition, Compression, and Transport

Martin Vetterli

EPFL and UC Berkeley
http://lcavwww.epfl.ch/~vetterli/

joint work with:
T.Ajdler, A.Chebira, R.Cristescu, I.Maravic (EPFL)
P.L.Dragotti (Imperial), M.Gastpar (UCBerkeley)

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 and transmission**
   - Slepian-Wolf, data gathering trees and distributed KLT

5. **Uncoded transmission**
   - simple yet powerful

6. **Sensor networks and source-channel coding**
   - to separate or not to separate

7. **Conclusions**

Acknowledgements

- Swiss and US NSF
- The National Competence Center on Research ''Mobile Information and Communication Systems''
- K.Ramchandran and his group at UC Berkeley
- The reading group at EPFL (IP1 & IP7)
- IP2 (E.Telatar) and IP3 (B.Rimoldi)

The Swiss National Competence Center on Research ''Mobile Information and Communication Systems'' http://www.mics.org

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

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

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

- distributed signal aquisition
- 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

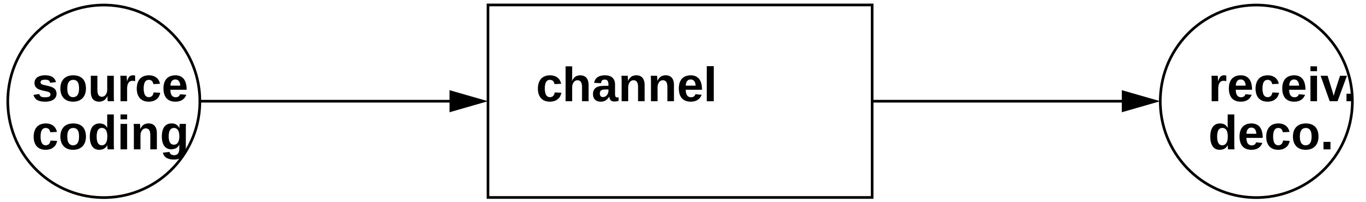
Communication is everywhere

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

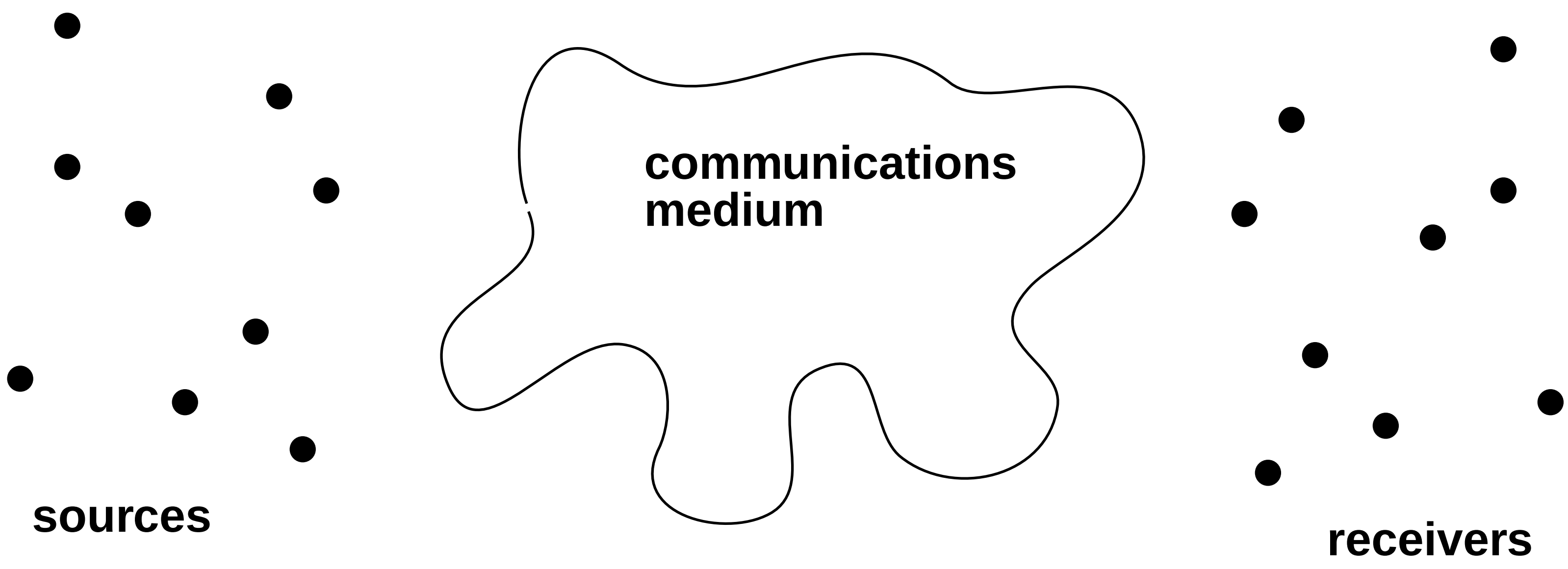
This creates a new challenging set of signal processing and communications problems

The Change of Paradigm

Old view: one source, one channel, one receiver



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



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)
- monitoring (multi-camera systems)
- virtual reality systems (synthesis)

2. Wireless sensor networks

Trade-offs between

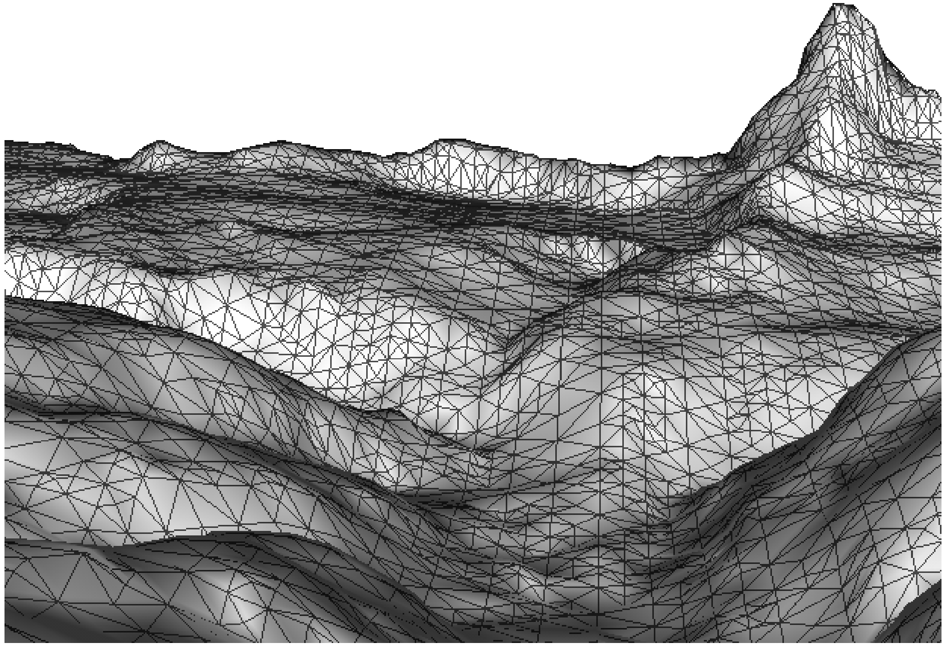
- aquisition accuracy
- computational power
- transmission power
- delay
- accuracy etc

Characteristics

- very low power
- fixed but unknown location
- constrained traffic patterns
  - data gathering
  - broadcast
- self-organized

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!

Good Questions?

Physical process governing the signals to be sensed

- what PDE is at work?

Sampling of the distributed signal

- are there spatial sampling theorems?
- are there good representations, approximations?

Dependent source coding

- can correlations be used for efficient compression?
- how does source structure influence communications structure?

Communications

- this is the archetypical multiterminal challenge
- is separation warranted (no)
- are bits any good anymore (not sure...)

Reconstruction

- full signal?
- estimation?
- control?

3. Interesting data sets and their structure

3.1 The Plenoptic Function [Adelson, Shum etc]

Multiple camera systems

- distributed signal aquisition
- 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

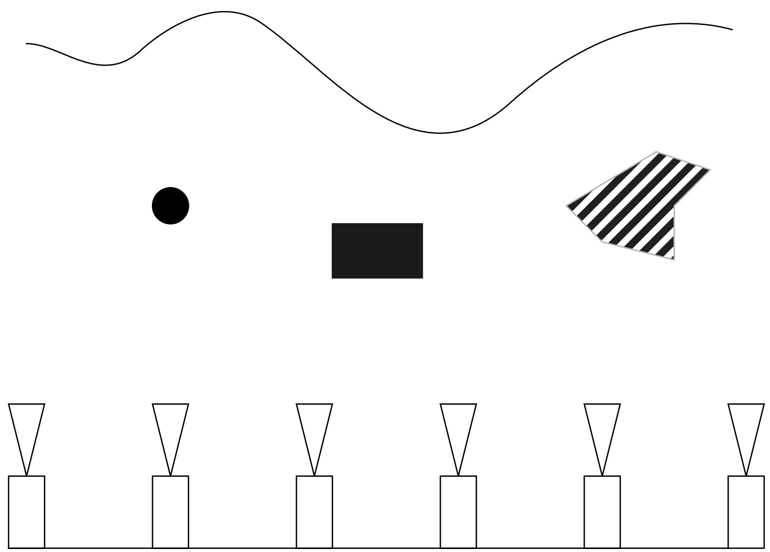
Implications on communications

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

An example (still from the Alps)

On Plenoptic Sampling

Model



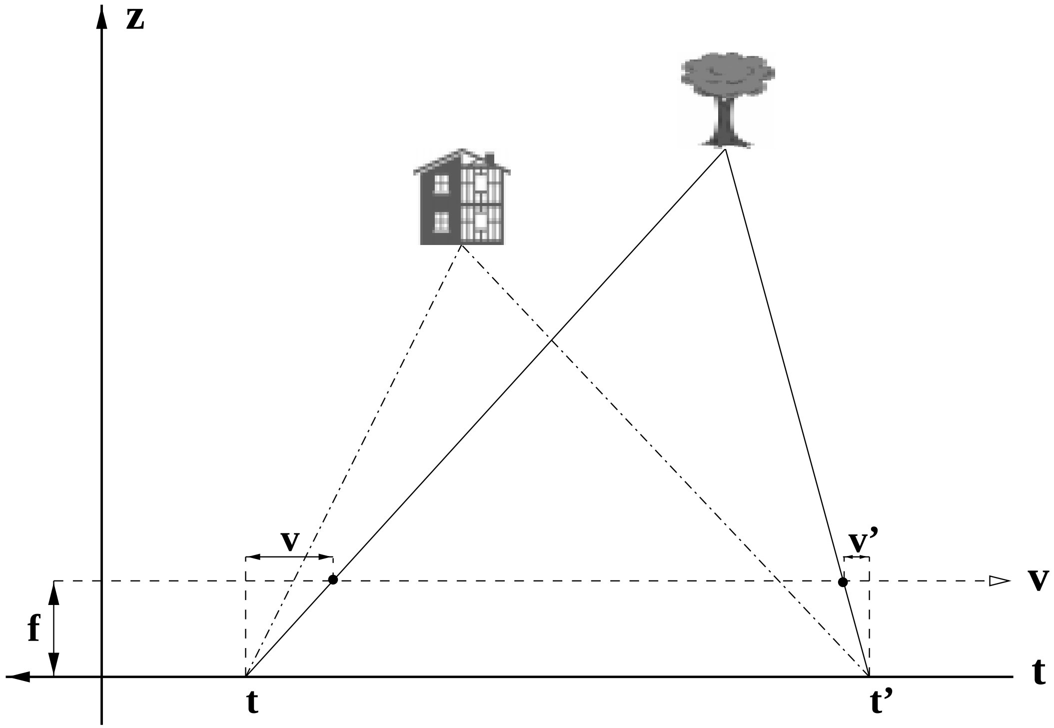
Questions:

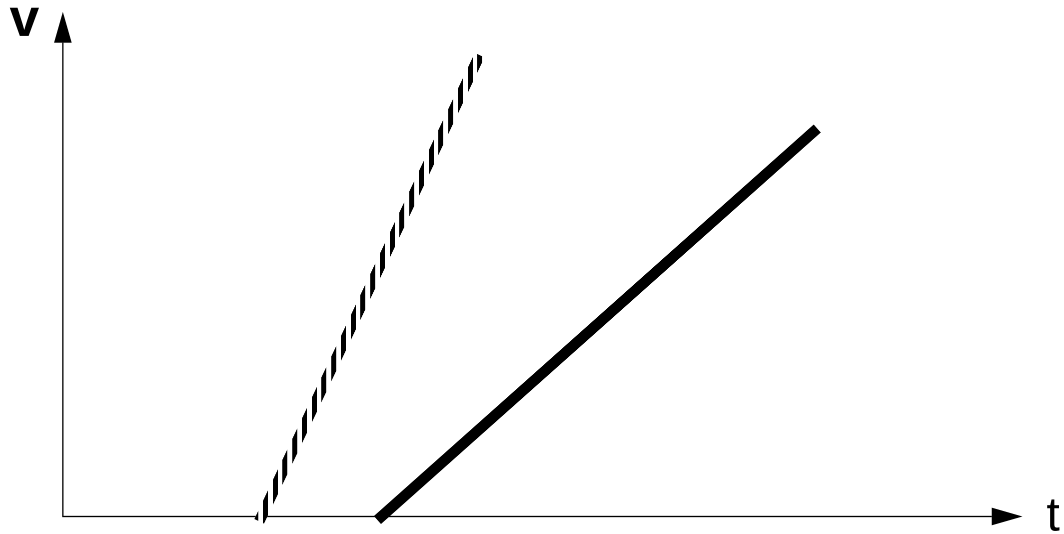
- how many pictures are ‘’enough’’ to interpolate any view?
- how to interpolate between the cameras

Plenoptic function

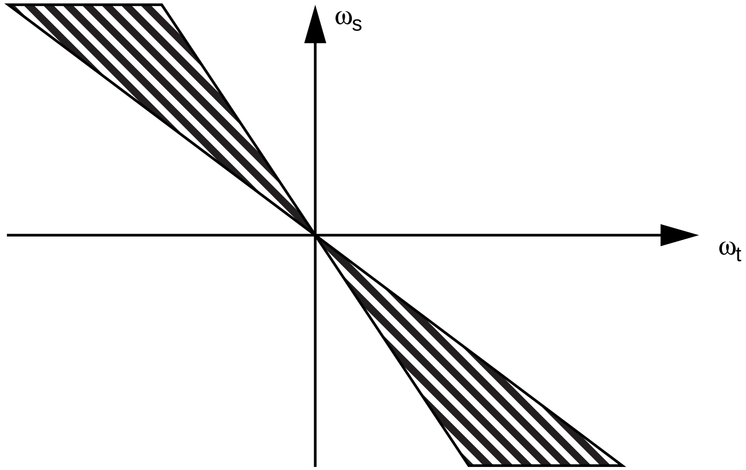
- is it bandlimited? (no...)
- how to approximate it
- implications on correlated source coding

The Plenoptic Function



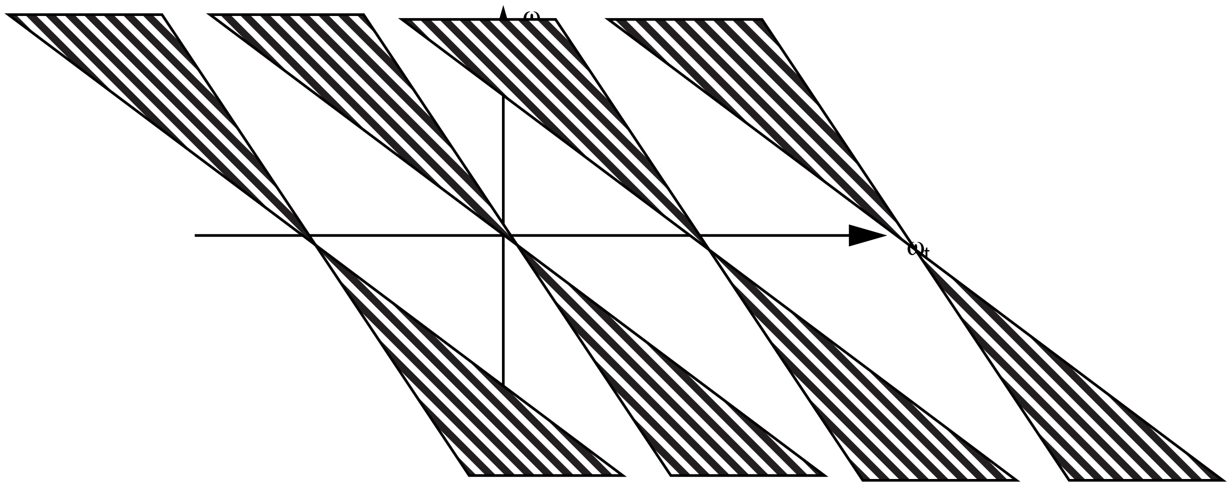


Fourier transform (approx.):



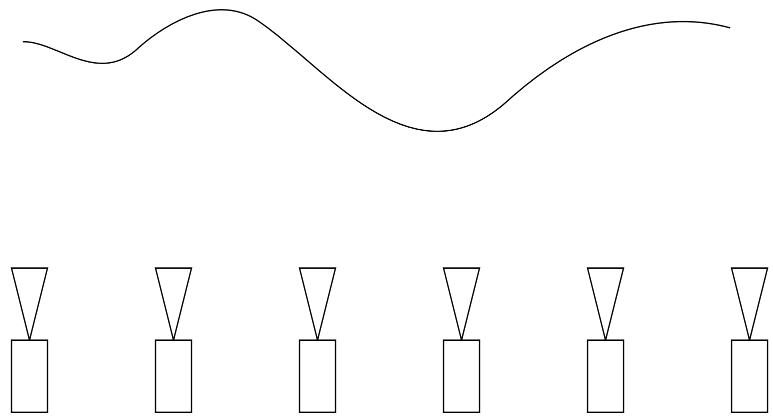
angle depends on depth of field.

Sampling [Shum et al]:



Examples of recent results

1. Bandlimited walls/fcts



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

Proof: FM modulation! leads to Bessel functions

2. Plenoptic function of finite complexity objects

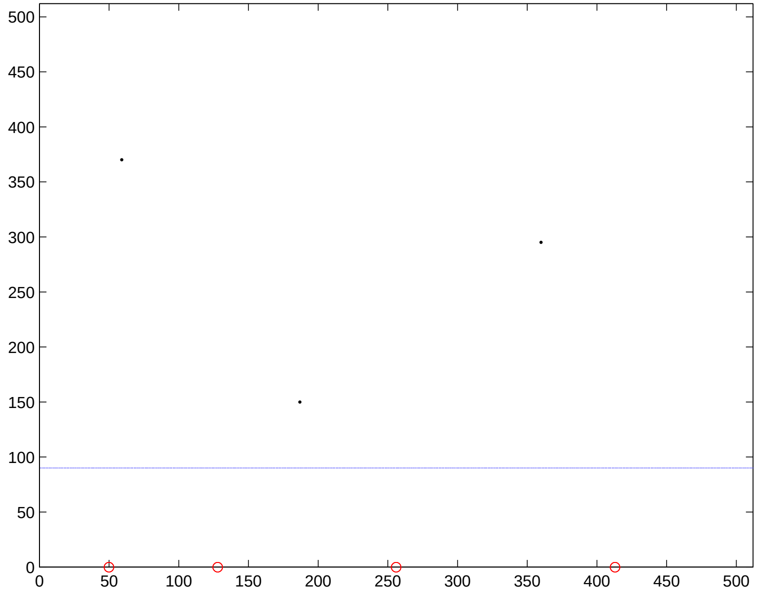
[Maravic et al] For certain ''simple scenes'' (collection of Diracs), the plenoptic function can be sampled with

- finite number of cameras
- finite number of samples

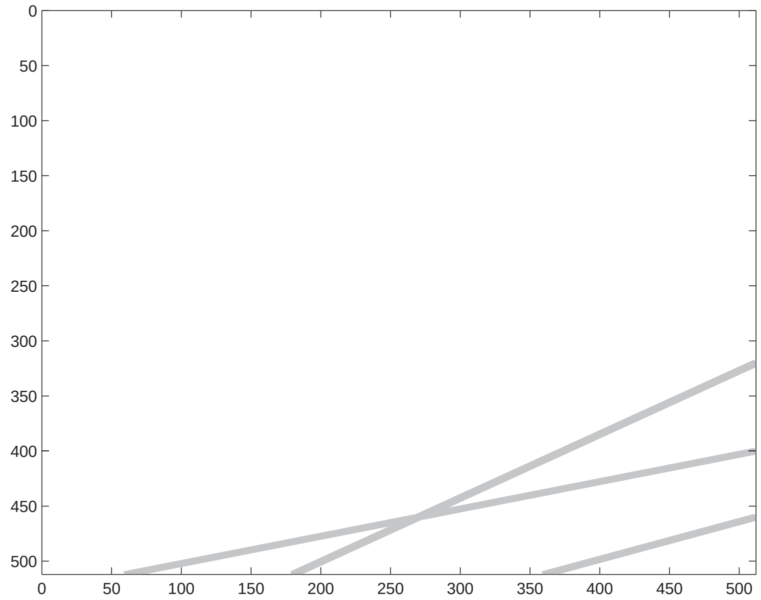
and reconstructed perfectly.

Proof: Radon transform + sampling of FRI signals

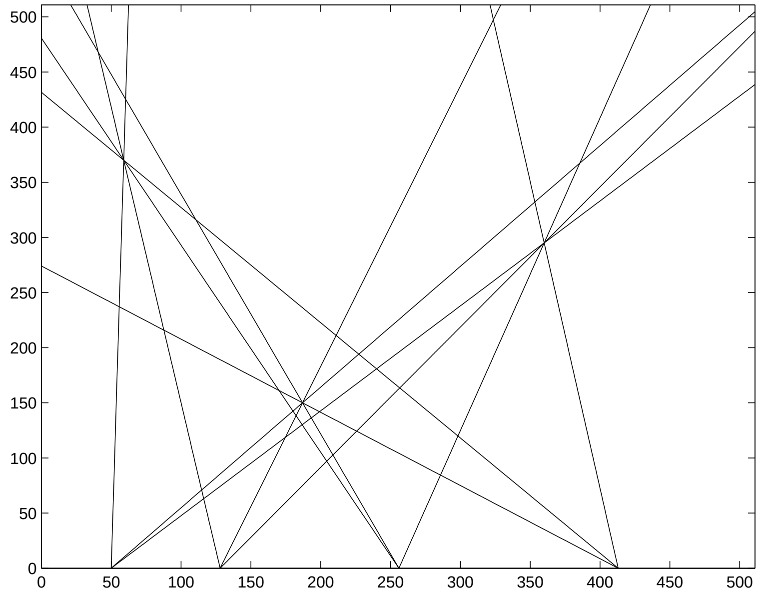
Example:



3 Diracs



Lowpass plenoptic function



Perfect backprojection

3.2 The plenacoustic function [AjdlerV:02]

Multiple microphones

- distributed signal aquisition 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

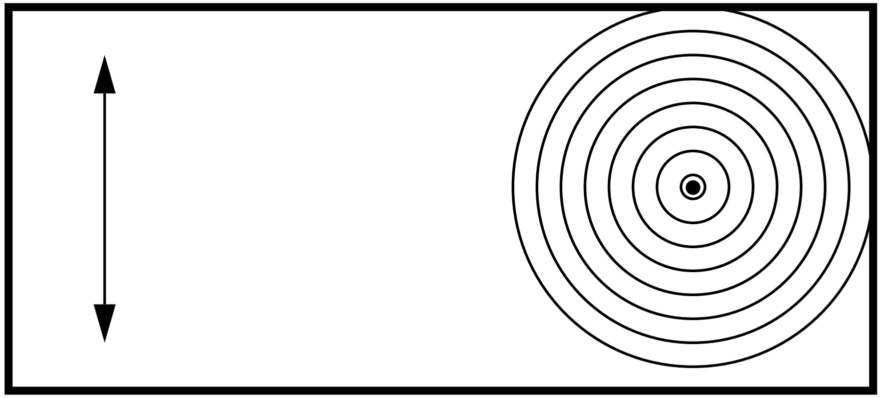
Implications on communications

- 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

Plenacoustic function and its sampling

Set up:

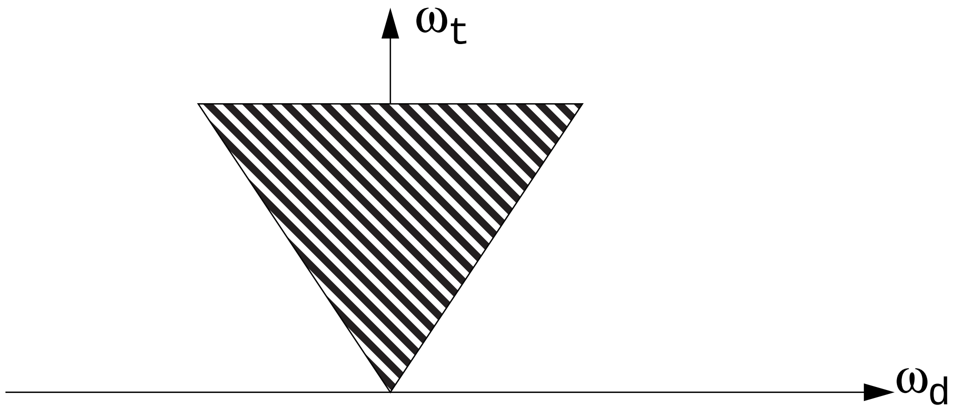


Can we sample with ‘’few’’ microphones and hear any location?

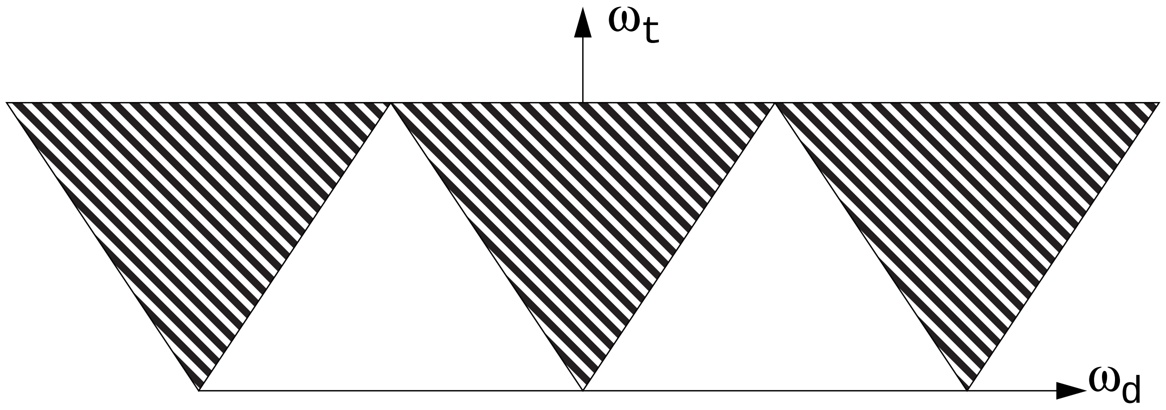
In this simple case, one could solve the wave equation, but in general, it is much simpler to sample the plenacoustic fct

Dual question also of interest

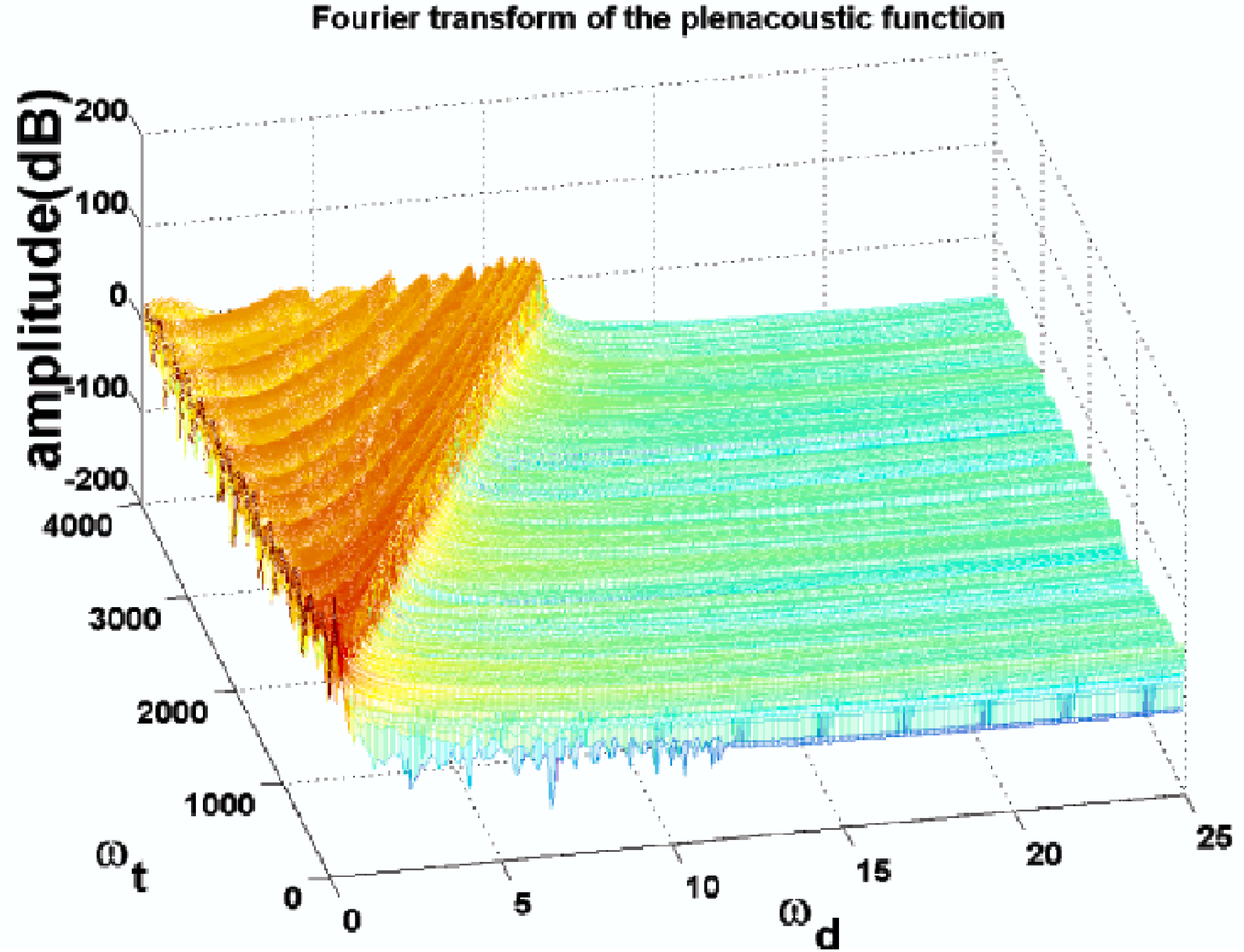
Plenacoustic function in Fourier domain (approx.):



Sampled version:



Example of a plenacoustic function



nice and bandlimited!

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?

Slepian-Wolf 1973

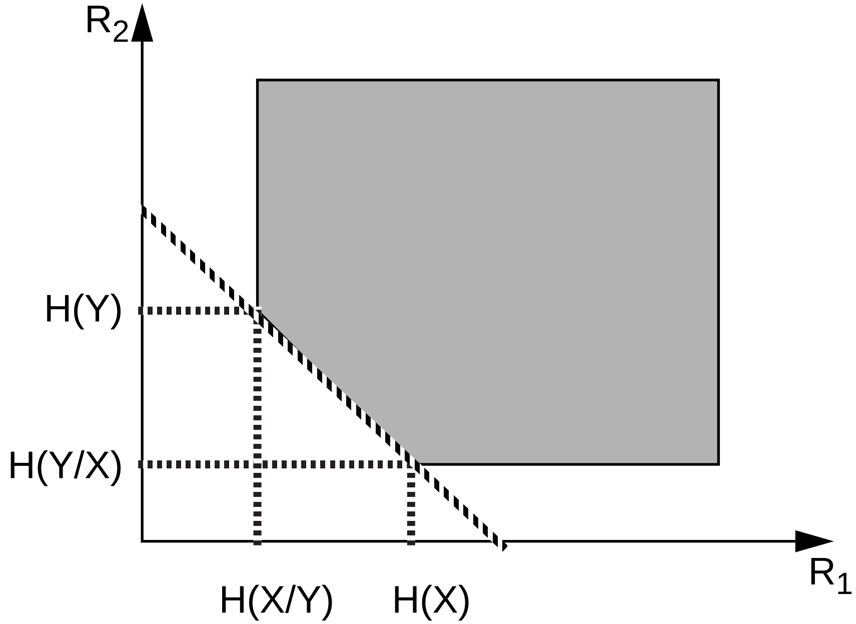
Given

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

Then: code separately, decode jointly

Achievable rate region

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



- for many sources...rather complex! (binning)

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

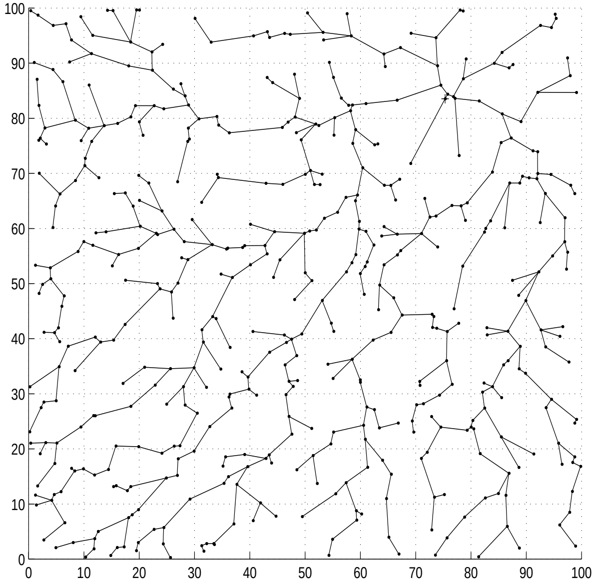
Results [CristescuV:02]

- Problem is in NP for $\beta < B$
- Good distributed heuristics
- Can make a large difference in power consumption

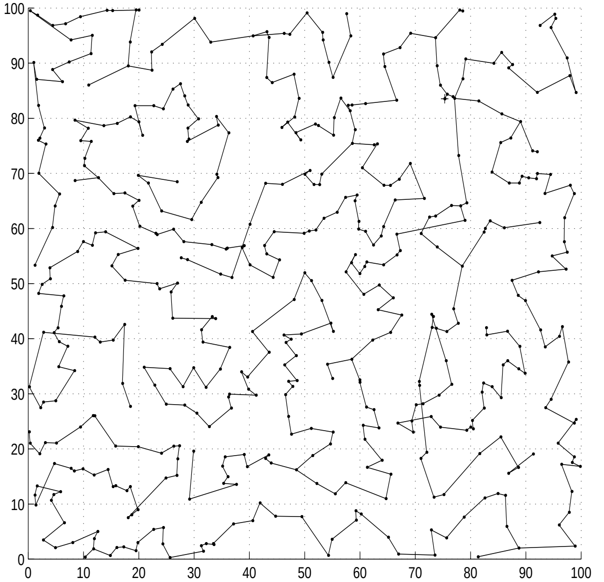
Main point:

- source structure influencescommunication structure

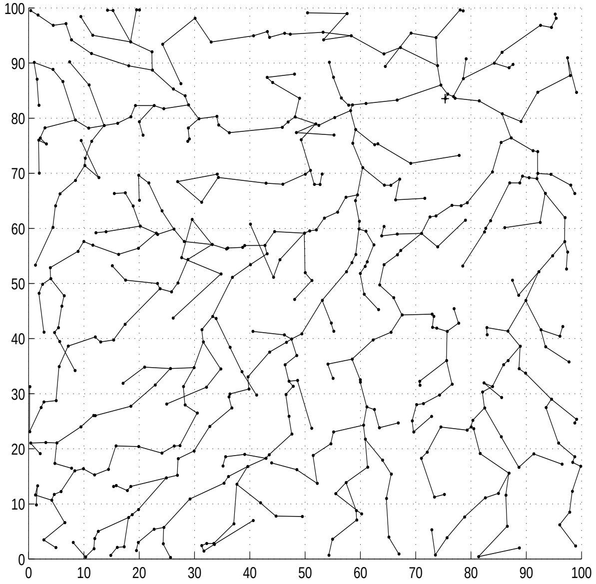
Example:



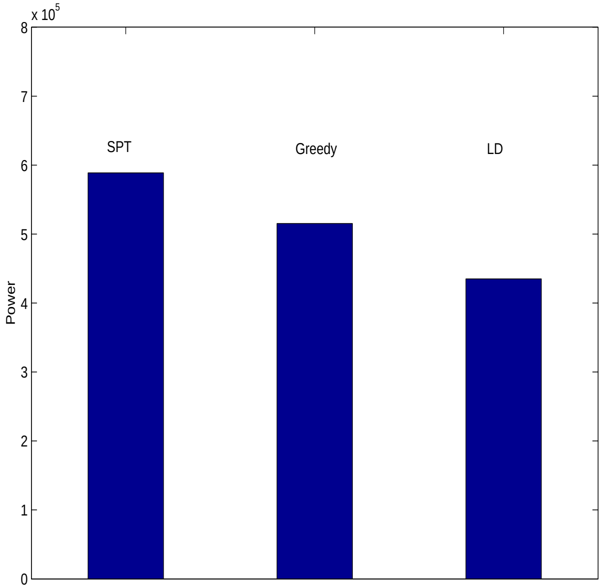
(a) SPT



(b) Greedy algorithm



(c) Leaves deletion heuristic

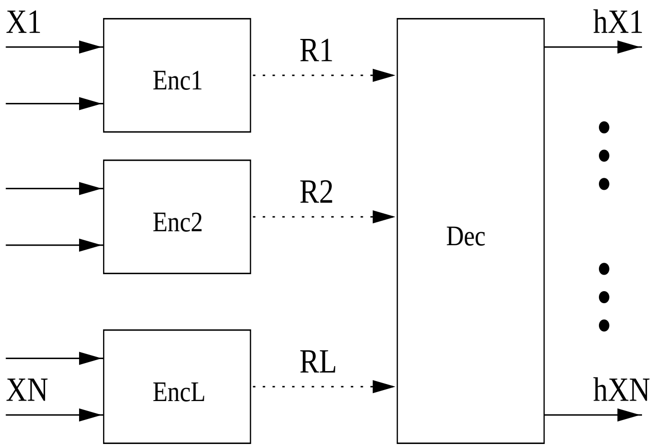


(d) Power efficiency

The Distributed Karhunen-Loeve Transform (DKLT) [GastparDV:02]

The Karhunen-Loeve transform is a key part of source compression

Assume a correlated vector source $[X_1, X_2, X_3, \ldots X_N]$ joint statistics (in particular second order) are known.:



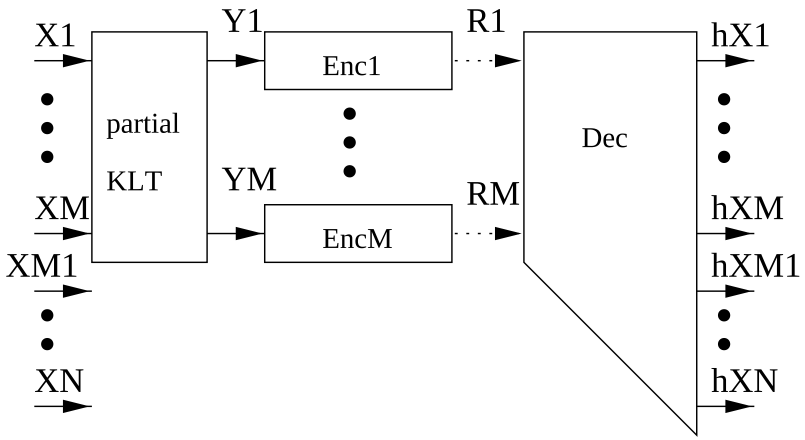
What is the best way to separately compress this source by L local compressors, for a joint decoder?

This answers (in part) a distributed source coding problem

Both non-linear approximation (NLA) and rate-distortion behavior are studied

The partial KLT

Assume only a part of the sources are observed, $[X_1, X_2, X_3, \ldots X_M]$ but the entire vector N > M needs to be reconstructed.



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

Results:

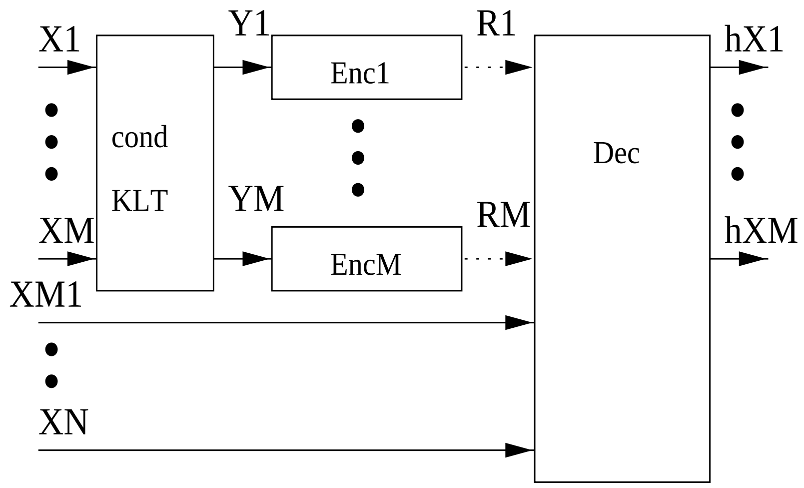
- NLA: k dim. approx. with largest modified eigenvalues

- Compression: R(D) similar to gaussian, with modified eigenvalues

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.



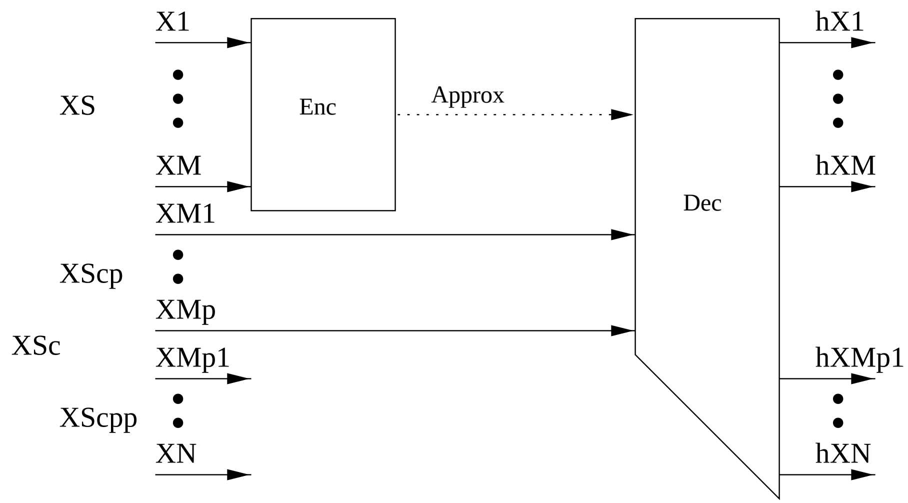
Cond. KLT: $C\ \Sigma_{s/\bar{s}}\ C^T = \mathrm{diag}(\lambda_i)$, that is, Y is conditionally uncorrelated

Results:

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

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

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

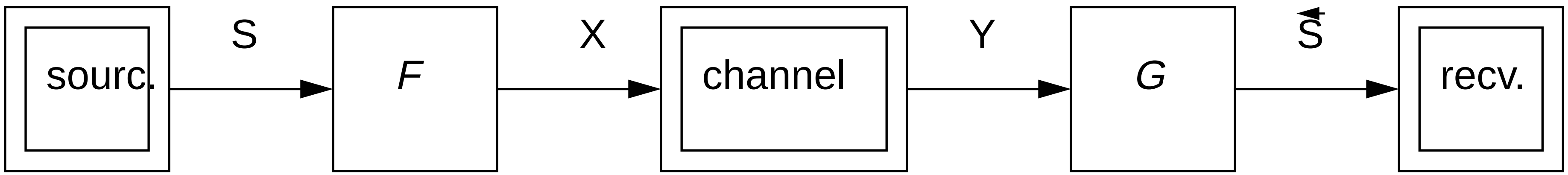
- easy way to achieve best performance

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: $\rho(x)$

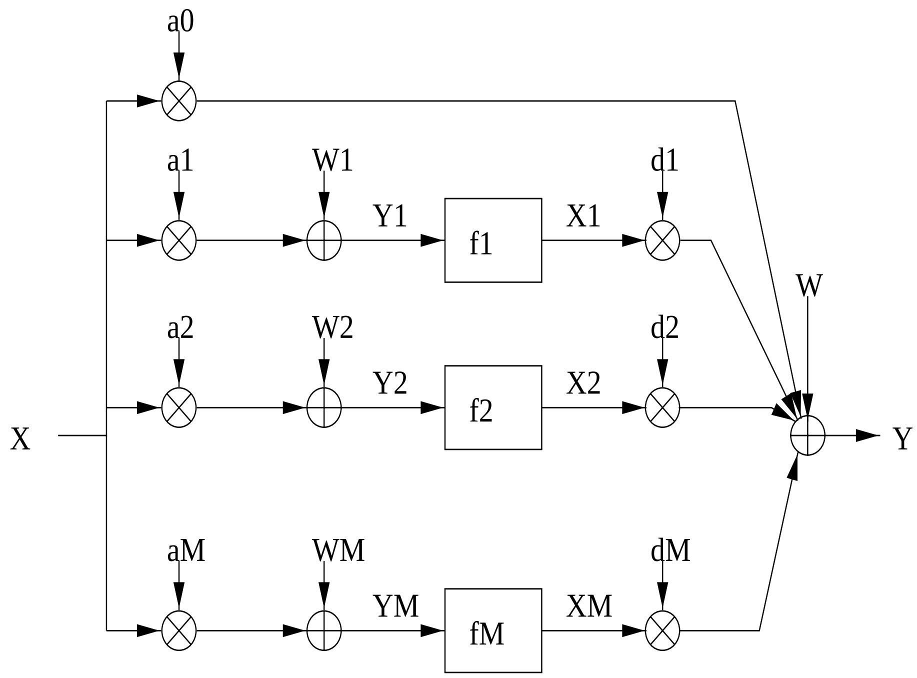
The art is measure matching!

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



Relay network [GastparV:02]

Old and partly open problem from IT

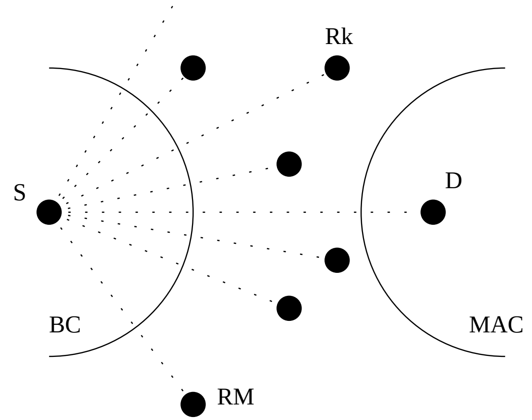


Simple model

Interesting question when the number of relays grows...

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

$$C = \log\left(1 + \frac{P}{N} \cdot \alpha\right)$$

- e.g. if each relay has power Q,

$$C = \log\left(1 + \frac{M \cdot Q}{N}\right)$$

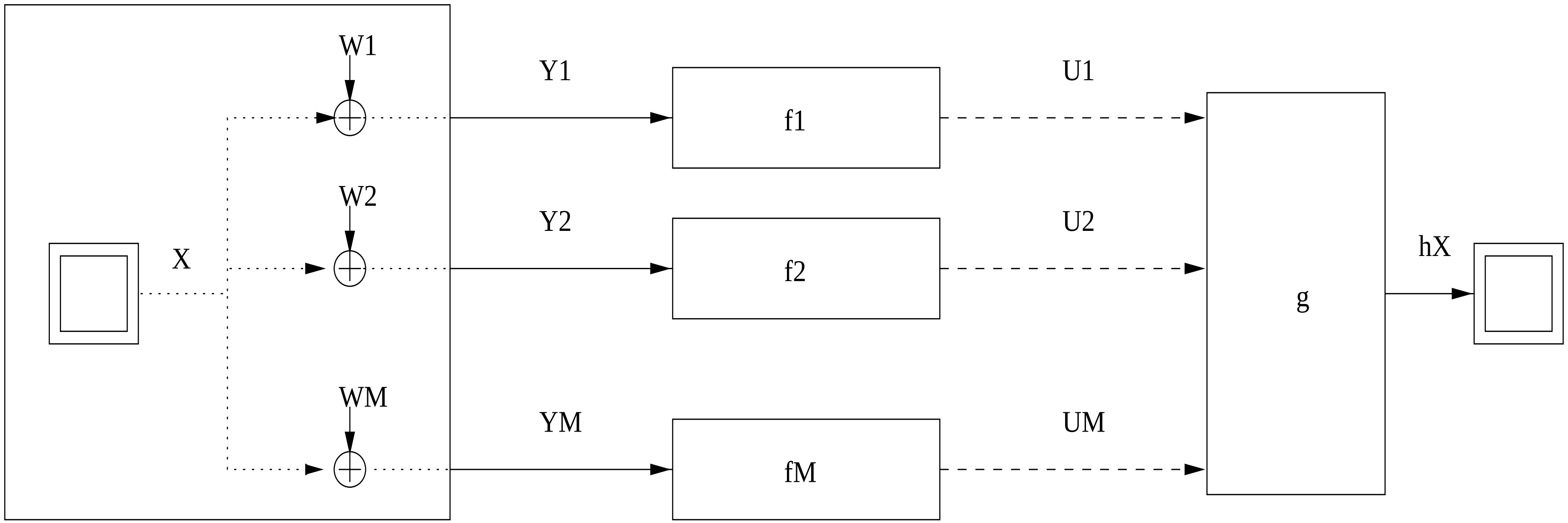
- this is different (and better) from other approaches
- method uses uncoded transmission

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

Consider the problem of sensing

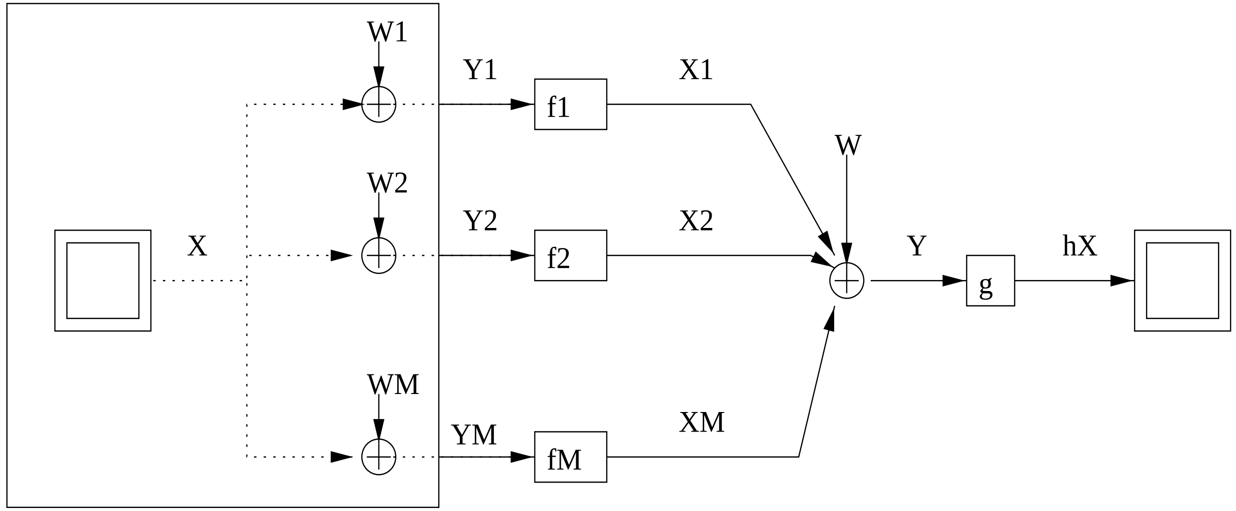
- one source
- many sensors
- reconstruct an estimate

Model: The CEO problem [Berger et al]



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

Example: Gaussian source σ_s^2, Gaussian noise σ_w^2



Performance:

- with uncoded transmission: $\text{MSE} = O\left(\frac{1}{M}\right)$
- with separation: $\text{MSE} = O\left(\frac{1}{\log M}\right)$!

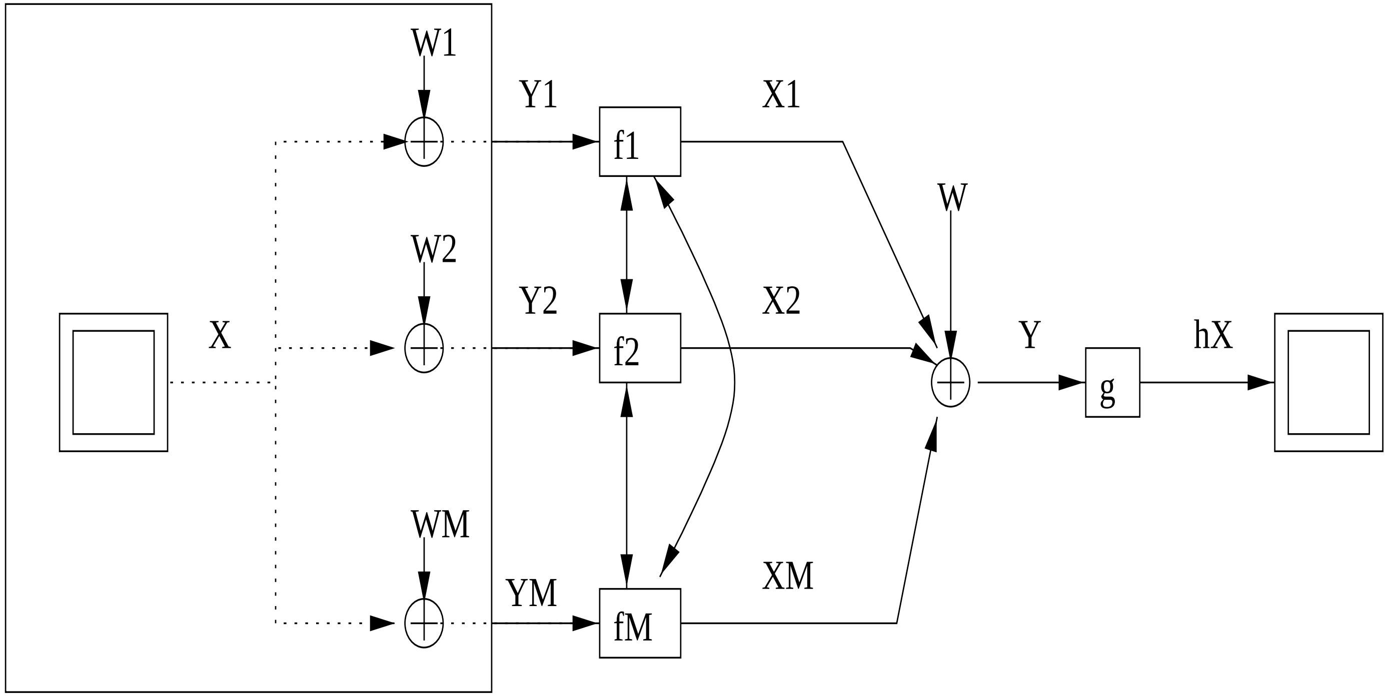
Can be shown to be optimum performance

Condition for optimality: measure matching!

- $d(X, \hat{X}) = -\log p(X/\hat{X})$
- $I(S, \overline{S}) = I(X;\ Y_1,\ Y_2,\ \ldots,\ Y_M)$

Can be generalized to many sources $X_1, X_2, \ldots, X_N$

It is the best one can do!



Communication between sensors does not help as M grows

Intriguing remark:

- by going to ‘’bits’’, MSE went from 1/M to 1/Log(M)
- ‘’bits’’ might not be a good idea for distributed sensing and communications
- if not ‘’bits’’, what is information in networks? [Gastpar:02]

7. Conclusions

There are some good questions in the interaction of

- physics of the process
- sensing
- representation & compression
- transmission
- decoding

This goes beyond joint source-channel coding

- aquisition 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!

and remember: you might have to forget about ‘’bits’’ as a good exchange value in distributed information aquisition and communication!

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.
- A.Chebira, P.L.Dragotti, L.Sbaiz, and M.Vetterli, Sampling the plenoptic function, IEEE ICIP, submitted.
- T. Ajdler and M. Vetterli, The plenacoustic function, sampling and reconstruction, in Proc. IEEE ICASSP-03.
- 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. IEEE DCC 2003.
- M. Gastpar, B. Rimoldi, M. Vetterli. To code or not to code: lossy source-channel communication revisited, IEEE Tr. on IT, to appear.
- 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, Sensor networks workshop, 2003.
- M. Gastpar, To Code or not to Code, PhD Thesis, Communication Systems, EPFL, Fall 2002.