Studying the Second Heart Sound

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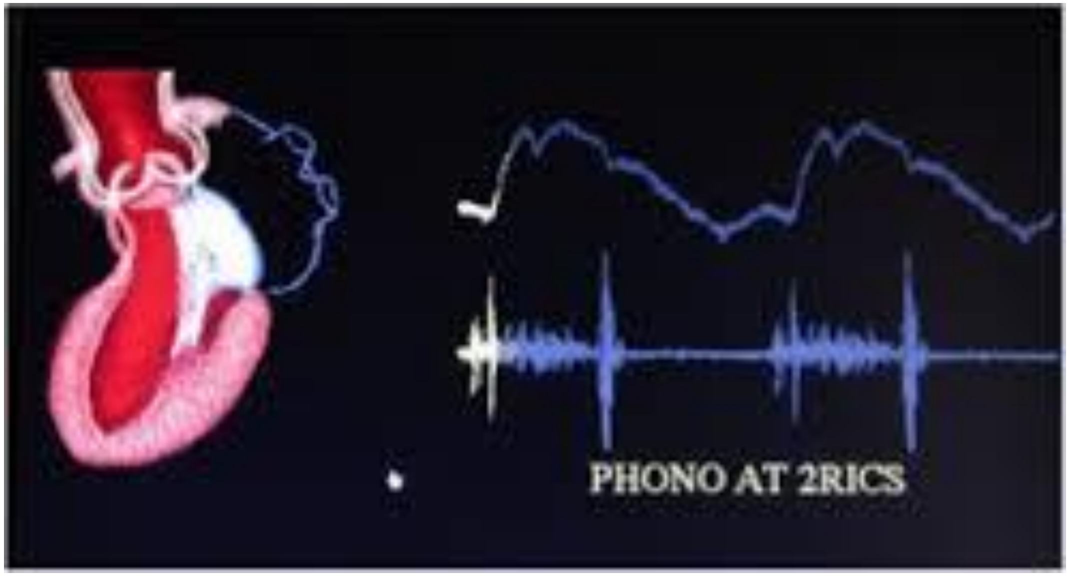
Seminários (Mest. Inf. Médica)

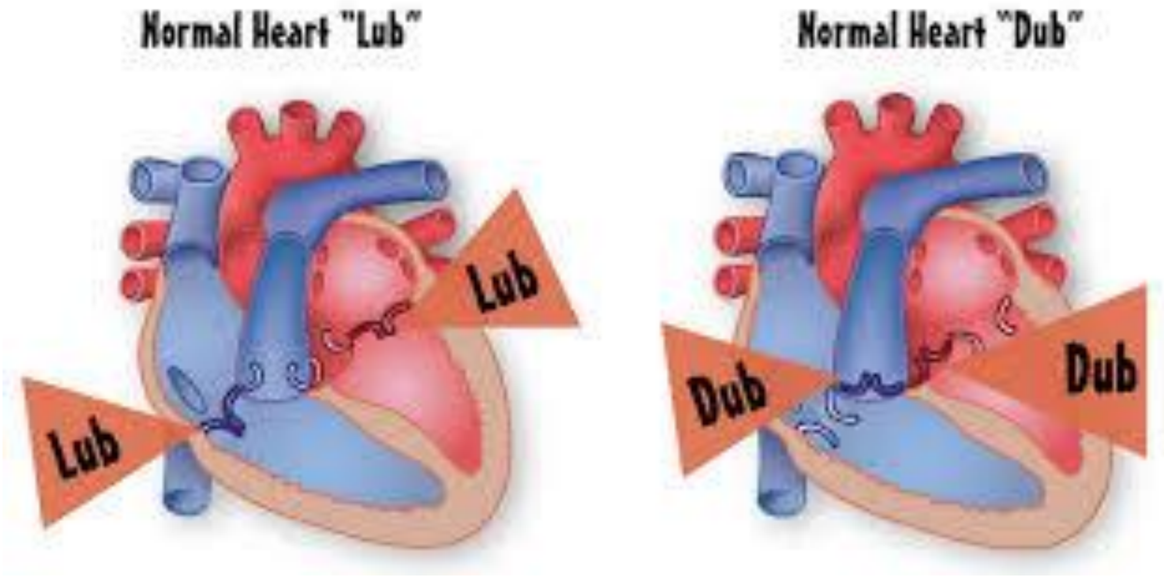
2014

- http://www.youtube.com/watch?v=CiEBNDaTFOc



HEART SOUNDS

- http://www.youtube.com/watch?v=2aO0HKIP3vI



QUESTIONS ?

- How many heart sounds are generated during a complete heart beat ?
- How many components have S2?
- The intensity of S2 is the same in all auscultation points?
- Why do I auscultate in so many points ?
- Why there is a split in S2?
- **Why is S2 important?**

Pathological split

- Split during expiration:

1. Aortic stenosis.
2. Hypertrophic cardiomyopathy.
3. Left bundle branch block (LBBB).
4. Ventricular pacemaker.

- Split during both inspiration and expiration

1. If splitting does not vary with inspiration. It is called a “fixed split S2” and it is usually associated to septal defect.
2. Continuous splitting with differents degrees during the respiration is an indication bundle branch block either LBBB or RBBB.

EXAMPLE – RADON TRANSFORM

- Tomography.
- Reconstruction using Projections.
- The Radon transform represents the projection data obtained as the output of a tomographic scan.

EXAMPLE – RADON TRANSFORM

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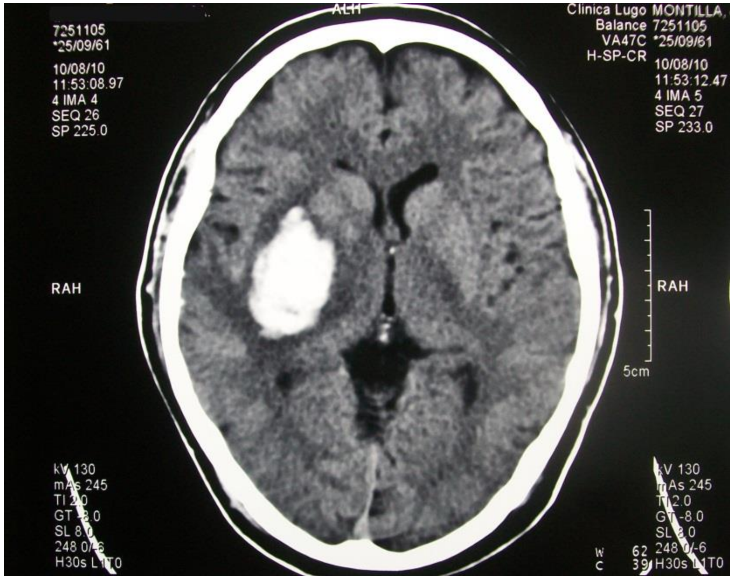
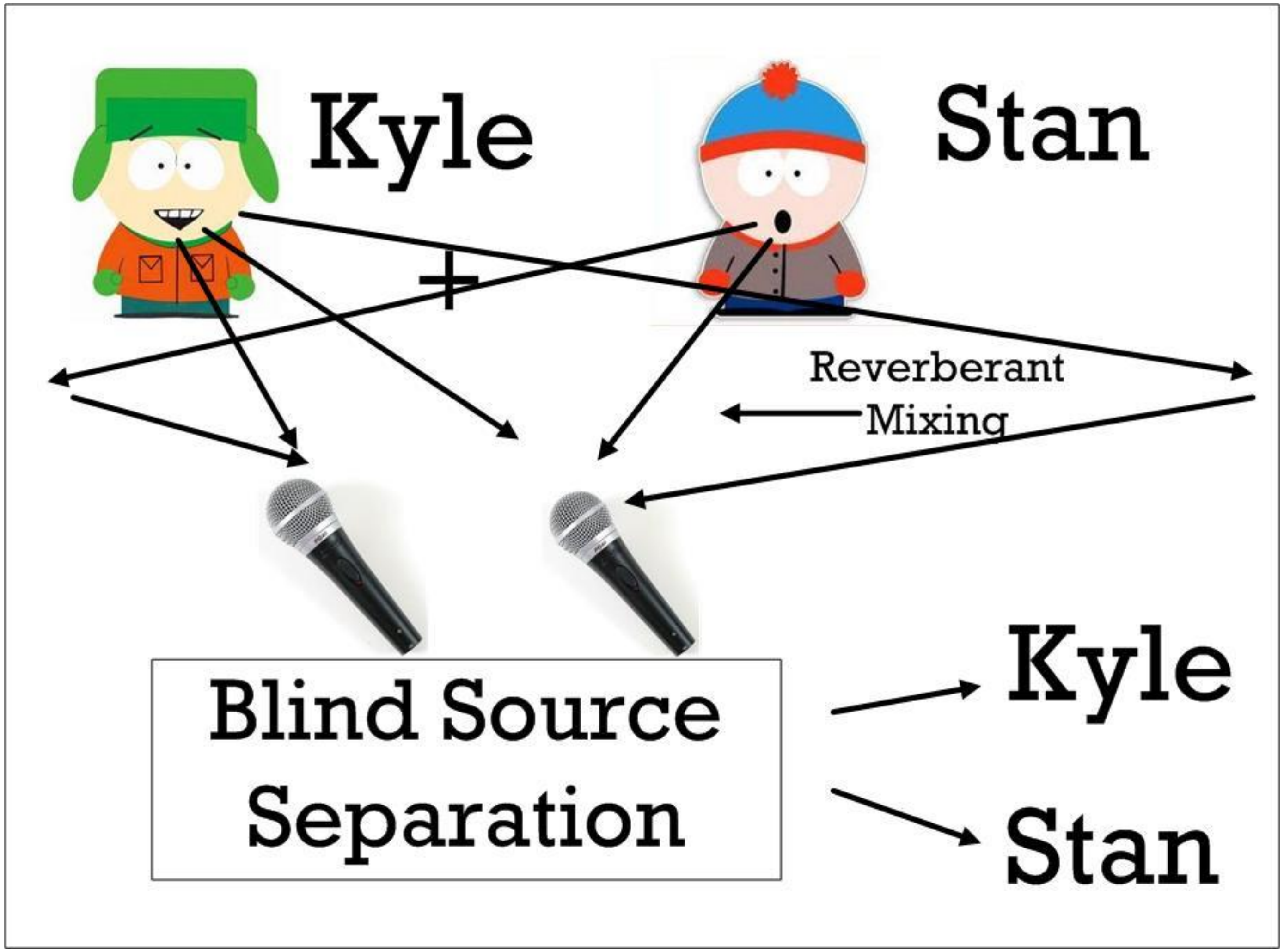
- The inverse of the Radon transform can be used to reconstruct the original density from the projection data.
- The Radon transform is the base of computed axial tomography.

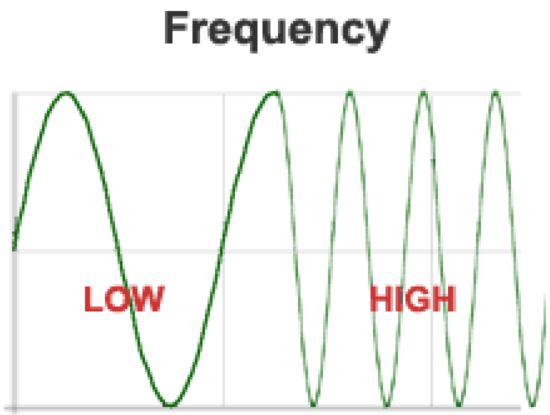


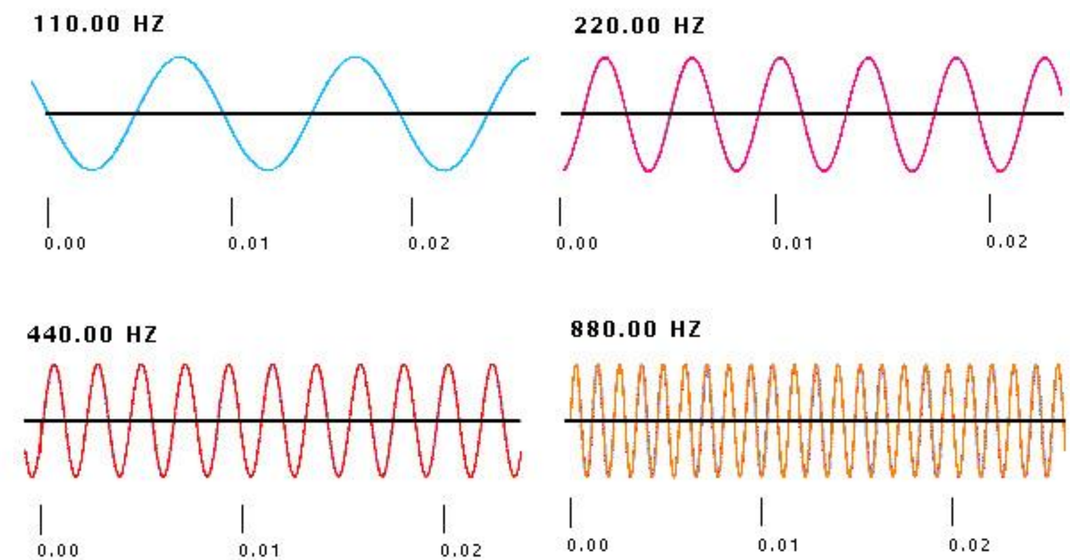
Source Separation: a usual problem?



Cocktail Party Problem

http://research.ics.aalto.fi/ica/cocktail/cocktail_en.cgi





With priors:

Signal and noise non overlapping –> Very simple !!

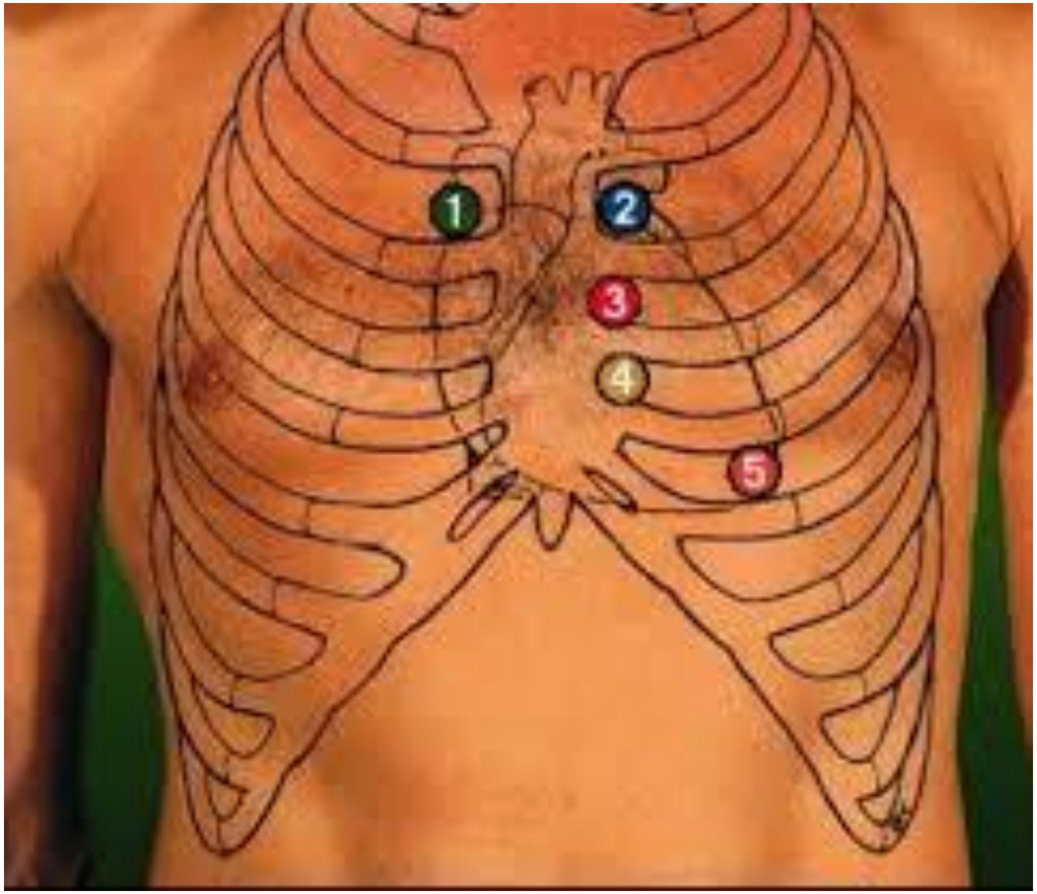
Without priors:

WHAT CAN WE DO ?

If the signal and the noise are in the same frequency range?

If one has no noise reference?

Source Separation: the fundamental Idea



Source Separation: the fundamental Idea

Assumption on Unknow mixtures:

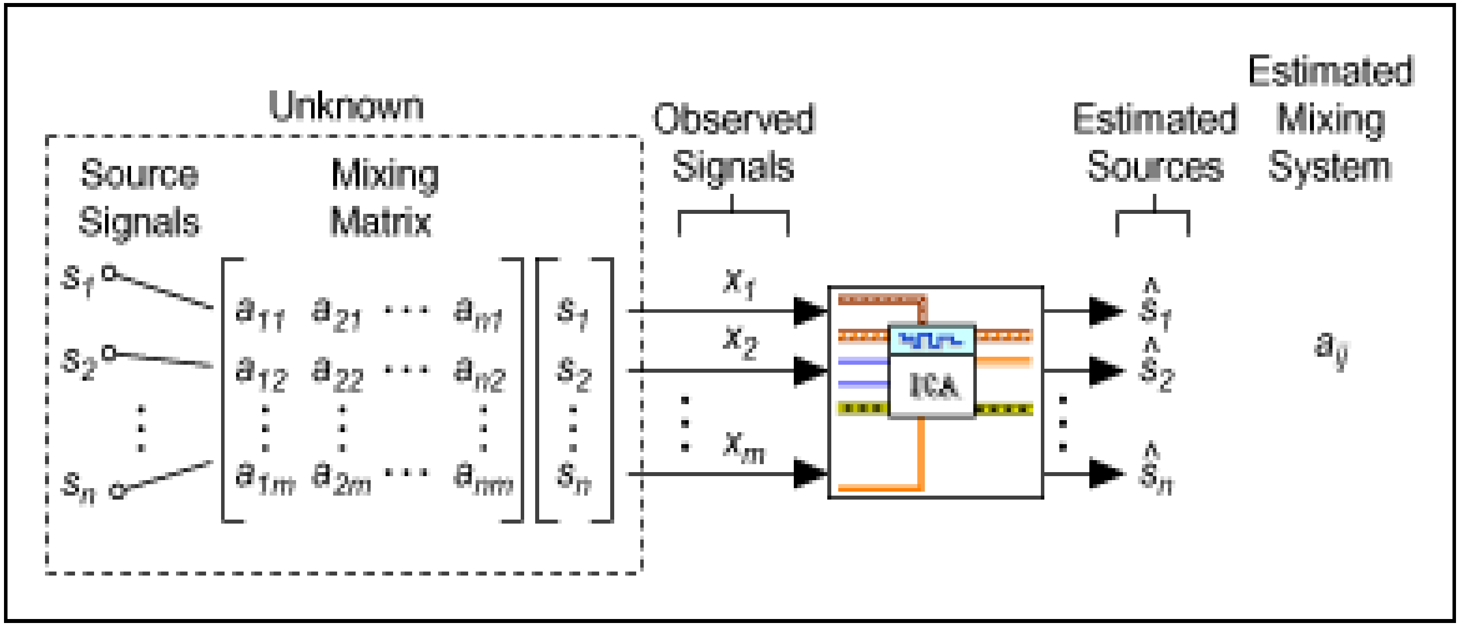
- Unknow mixtures are invertible (more sensors than sources).
- Non-linear mixtures.

Principles of the Solution

Direct: Estimate the Unknow Mixing from the observations

Indirect: Separating block, unmixed matrix.

Are these two matrices identifiable? How to estimate them ?


Unknown
Source Signals
Mixing Matrix
Observed Signals
Estimated Sources
Estimated Mixing System
ICA
a_{ij}

No Solution if.....

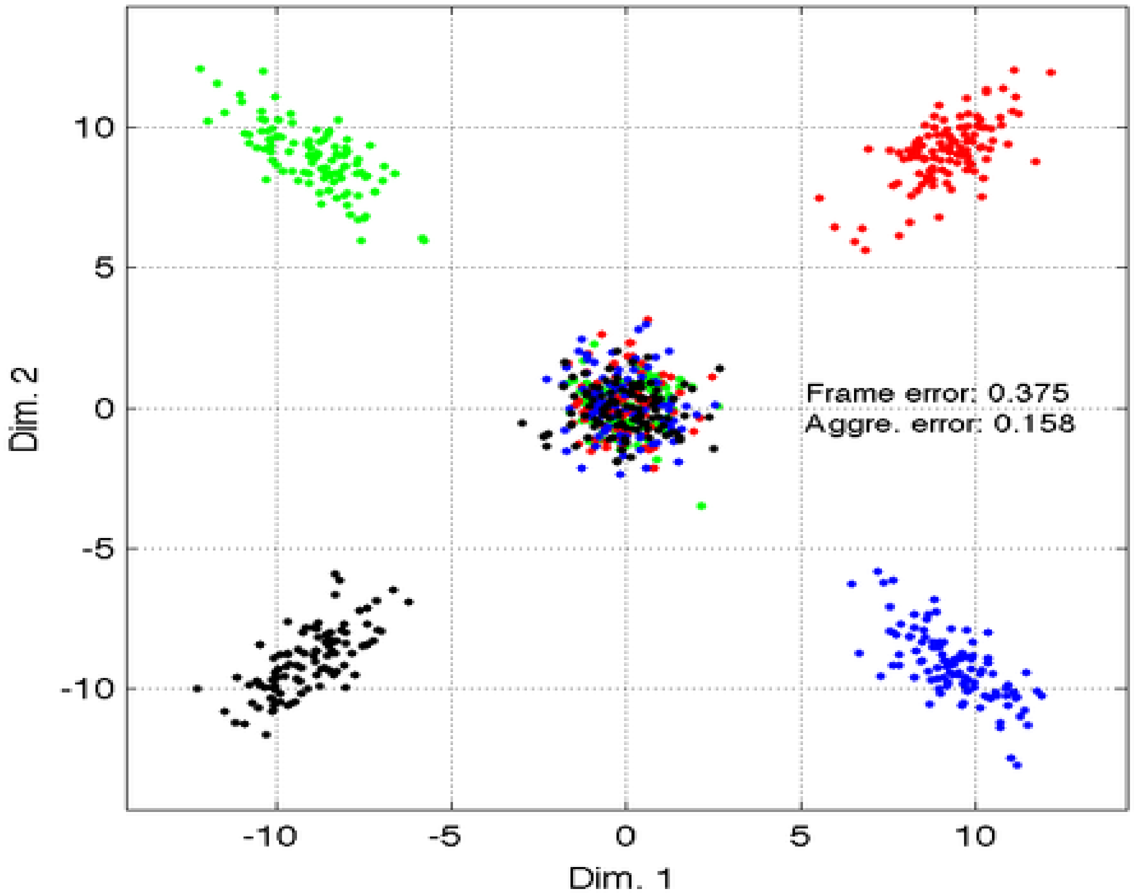
Linear Factorial Analysis:

- Linear mixtures $x = As$
- Assumption: components of the random vector s are mutually independent.

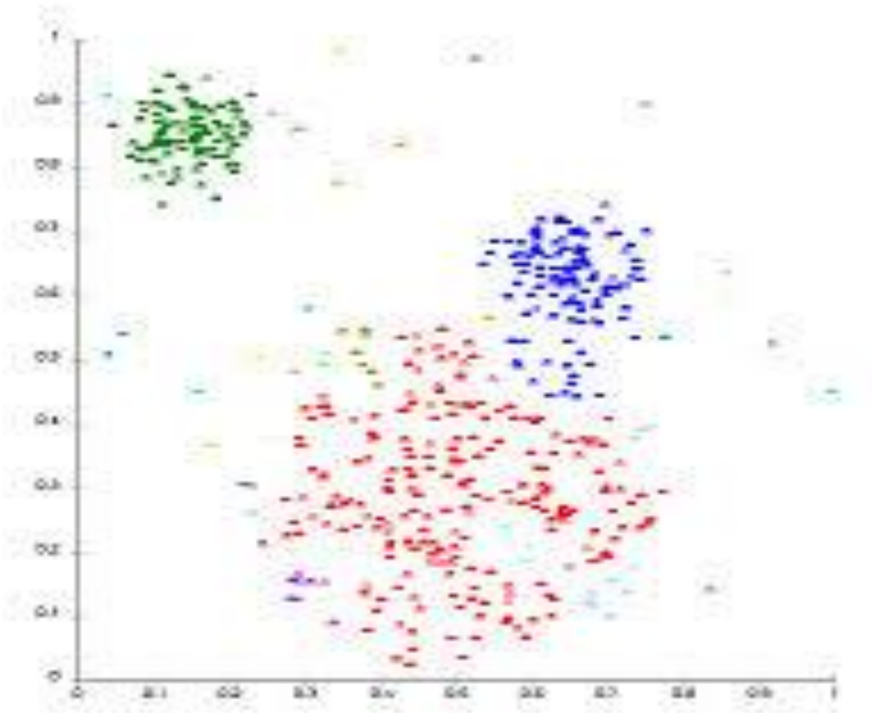
Theoretical Results:

- Separation is impossible if sources are independent and identically distributed(iid) and Gaussian.
- **Two directions for Separation**
- If sources are (iid) and NON Gaussian , ICA with HOS (High-order Statistic).
- If sources are NON iid and Gaussian with SOS (Second-order Statistics)
  - Temporally correlated sources.
  - Non stationnary sources.

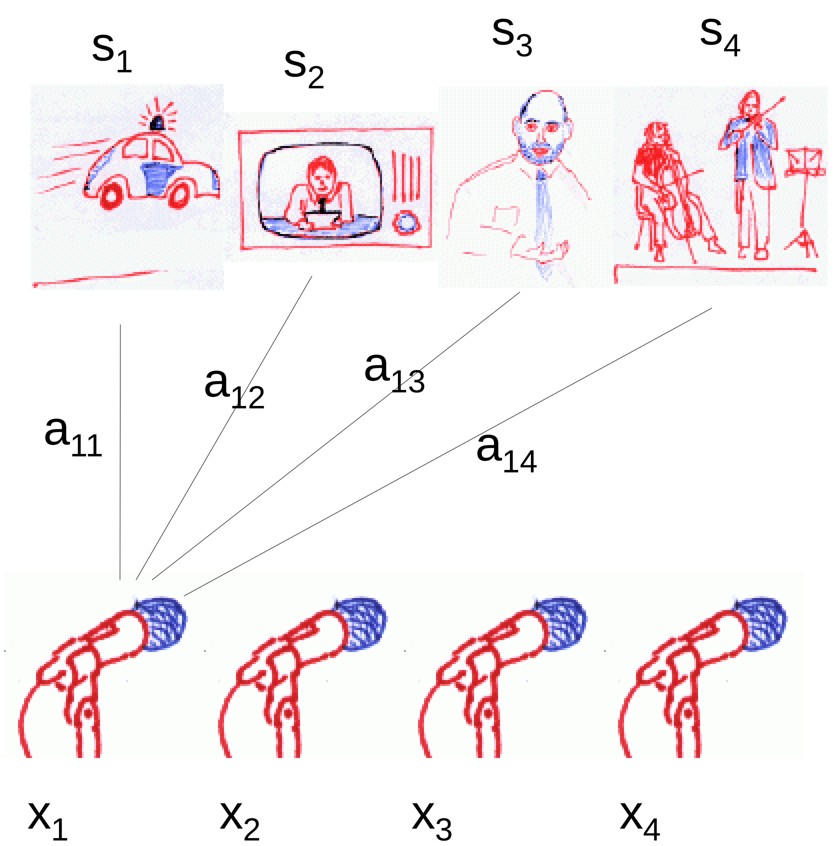
IID AND GAUSSIAN



NOT IID AND GAUSSIAN



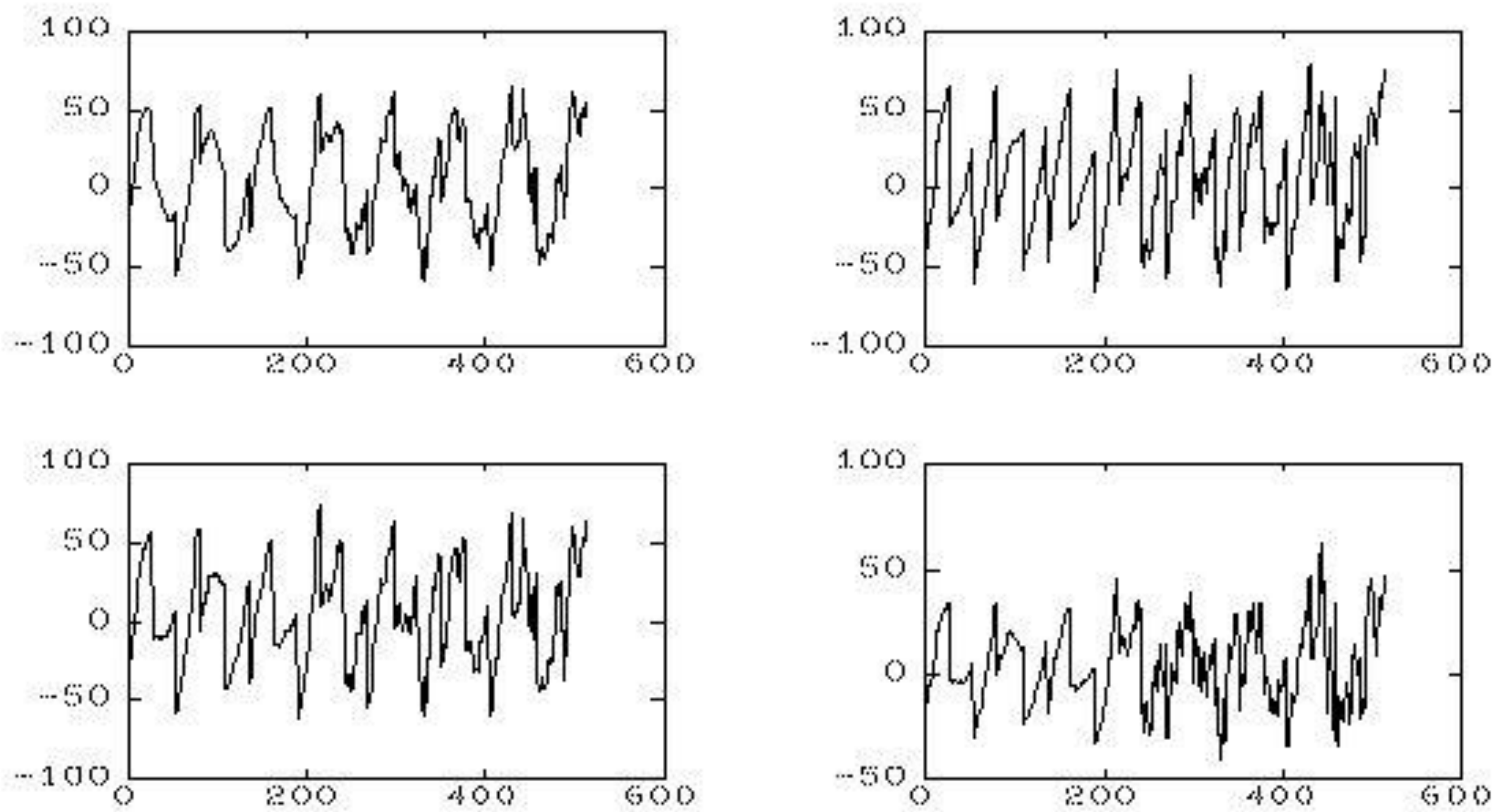
INDEPENDENT COMPONENT ANALYSIS
ICA MODEL



$x_i(t) = a_{i1}*s_1(t) + a_{i2}*s_2(t) + a_{i3}*s_3(t) + a_{i4}*s_4(t)$

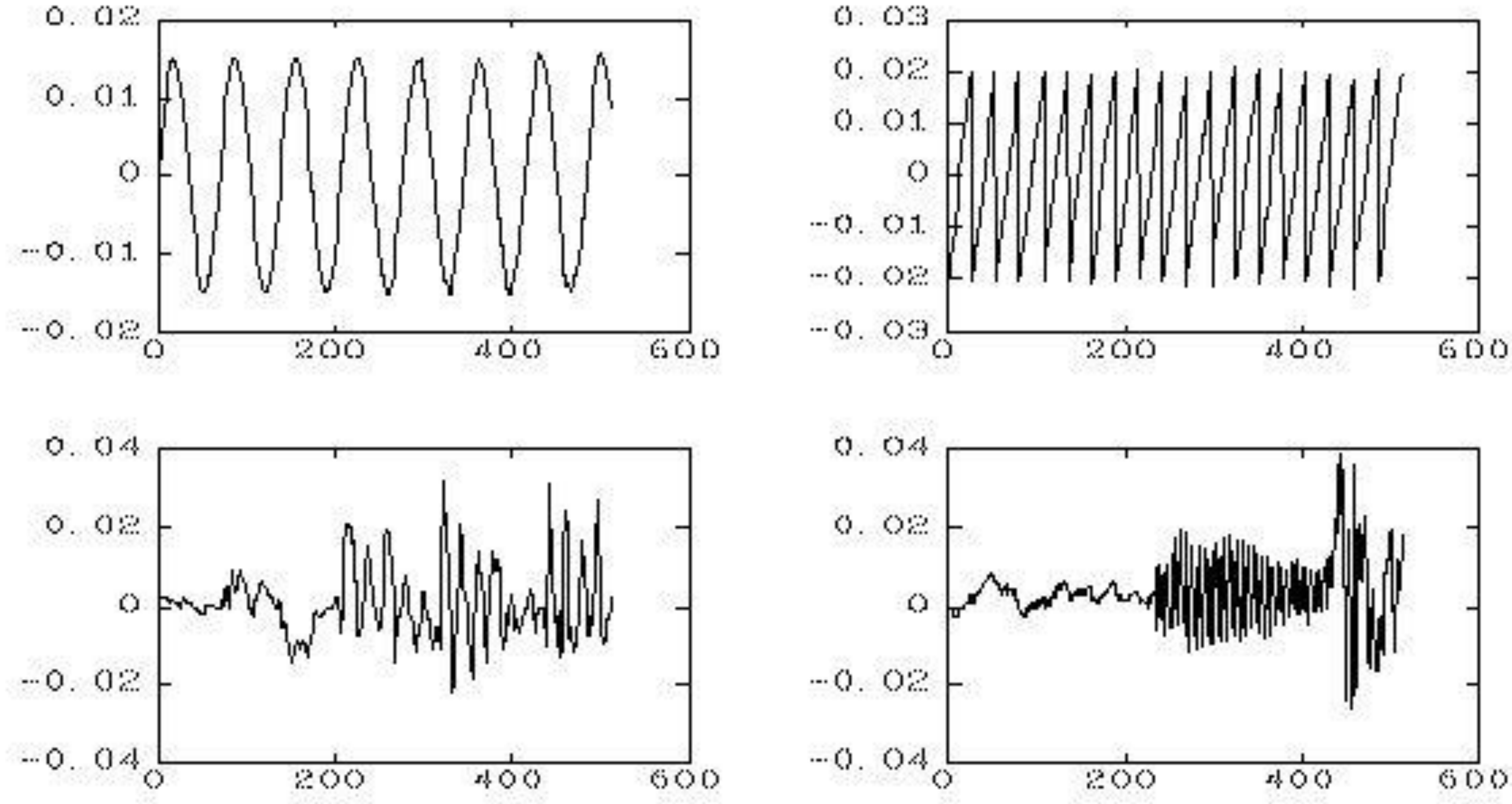
Here, i=1:4.

In vector-matrix notation, and dropping index t, this is
x = A * s



This is recorded by the microphones: a linear mixture of the sources

$x_i(t) = a_{i1}*s_1(t) + a_{i2}*s_2(t) + a_{i3}*s_3(t) + a_{i4}*s_4(t)$



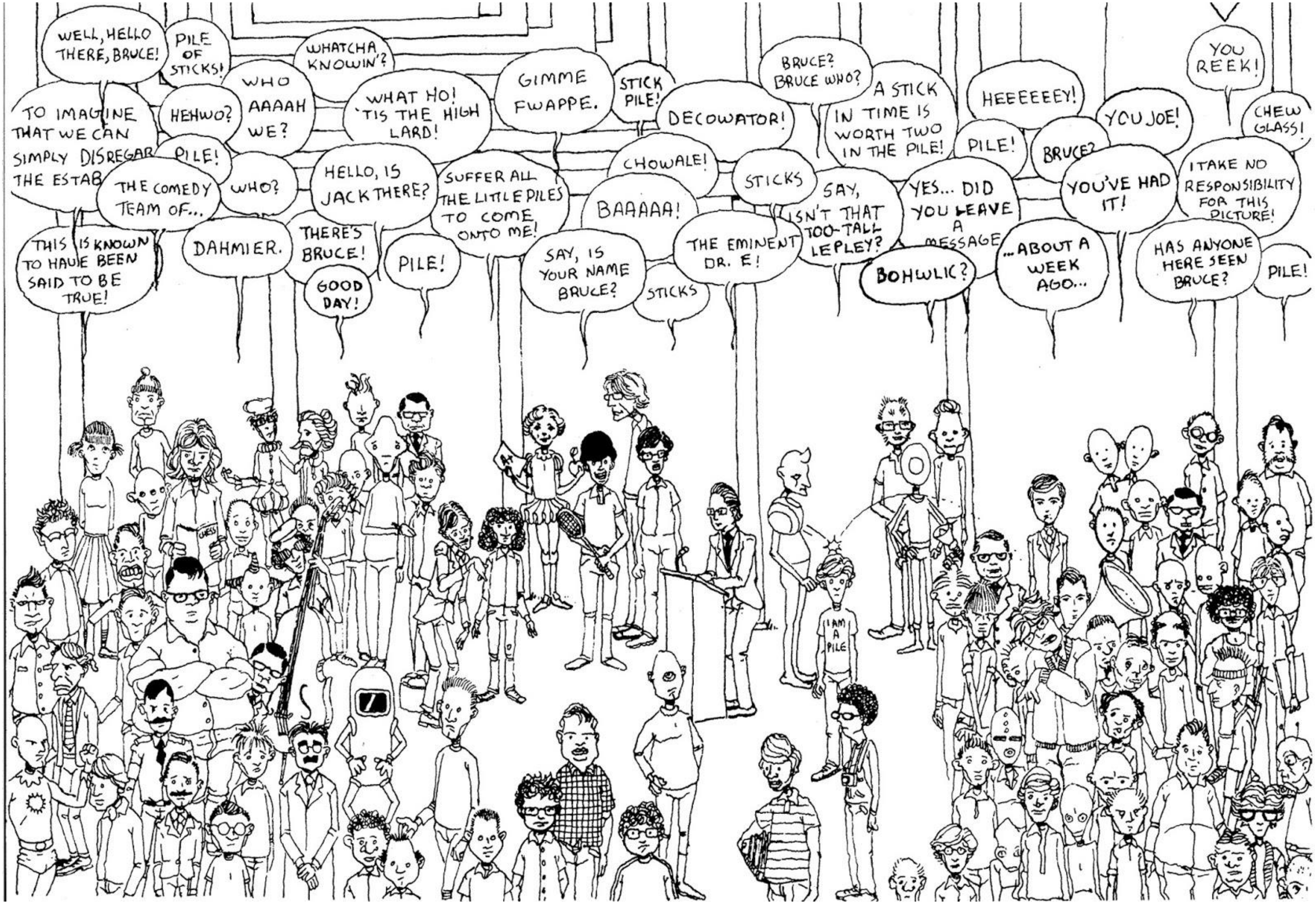
Recovered signals

Definition of ICA

- ICA Mixture model: $x = As$
  - A is mixing matrix; s is matrix of source signals
- Goal
  - Find some matrix W, so that

$$s = Wx$$

  - W = inverse of A



WELL, HELLO THERE, BRUCE!
PILE OF STICKS!
WHATCHA KNOWIN'?
WHO AAAAH WE?
HEHWO?
WHAT HO! 'TIS THE HIGH LARD!
GIMME FWAPPE.
STICK PILE!
BRUCE? BRUCE WHO?
A STICK IN TIME IS WORTH TWO IN THE PILE!
HEEEEEEY!
YOU REEK!
CHEW GLASS!
YOU JOE!
DECOWATOR!
TO IMAGINE THAT WE CAN SIMPLY DISREGAR THE ESTAB
PILE!
THE COMEDY TEAM OF...
WHO?
HELLO, IS JACK THERE?
SUFFER ALL THE LITTLE PILES TO COME ONTO ME!
CHOWALE!
BAAAAA!
STICKS
SAY, ISN'T THAT TOO-TALL LEPLEY?
YES... DID YOU LEAVE A MESSAGE
PILE!
BRUC
YOU'VE HAD IT!
I TAKE NO RESPONSIBILITY FOR THIS PICTURE!
THIS IS KNOWN TO HAVE BEEN SAID TO BE TRUE!
DAHMIER.
THERE'S BRUCE!
GOOD DAY!
PILE!
SAY, IS YOUR NAME BRUCE?
STICKS
THE EMINENT DR. E!
BOHWLIC?
...ABOUT A WEEK AGO...
HAS ANYONE HERE SEEN BRUCE?
PILE!
CHESS
I AM A PILE

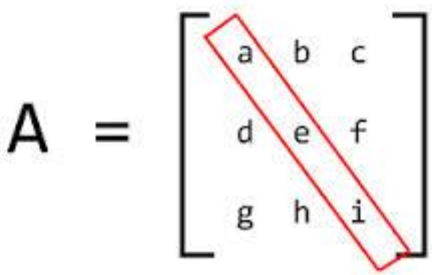
ICA: LINEAR INSTANTANEOUS MIXTURES

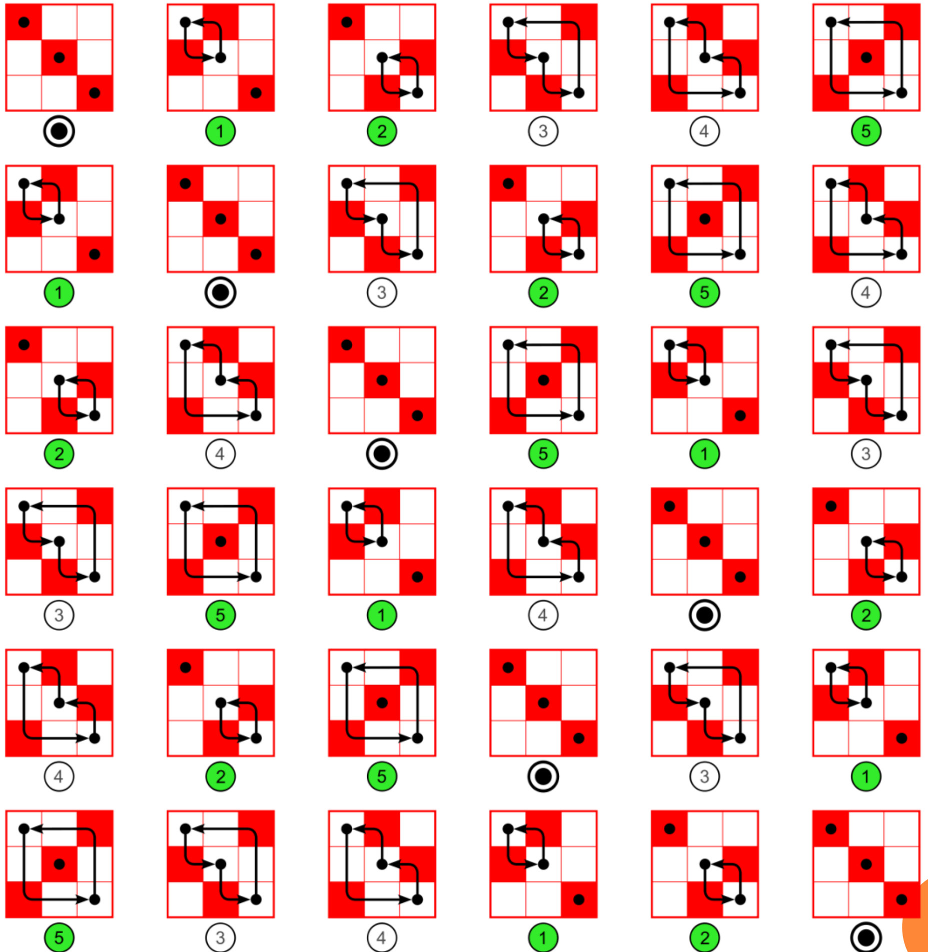
Theoretical Result:

Let $x(t) = As(t)$, where A is a regular matrix $s(t)$ is a source vector with statistically independent components, with at most one is Gaussian, then $y(t) = Bx(t)$ is a random vector with mutually independent components if and only if **BA=DP** , where D is a diagonal components and **P** is a permutation matrix.

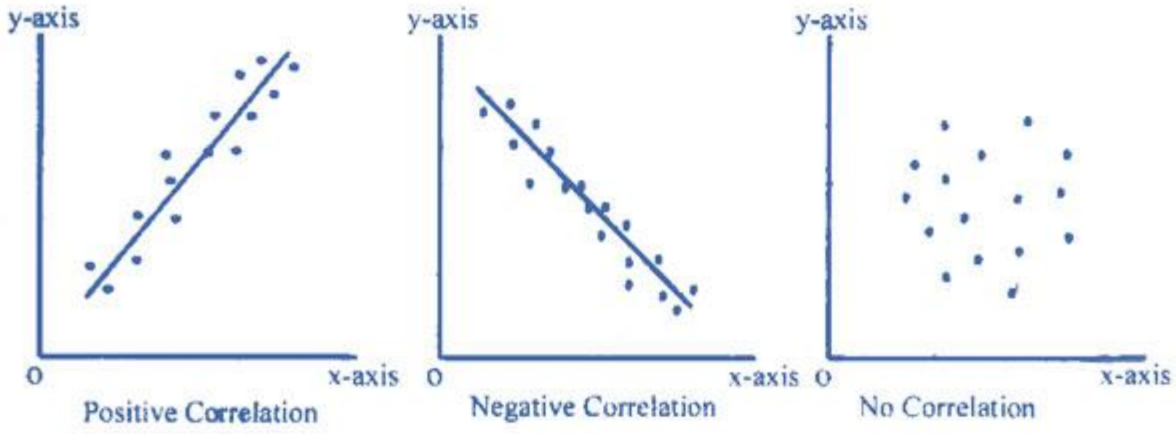
PERMUTATION AND DIAGONALIZATION

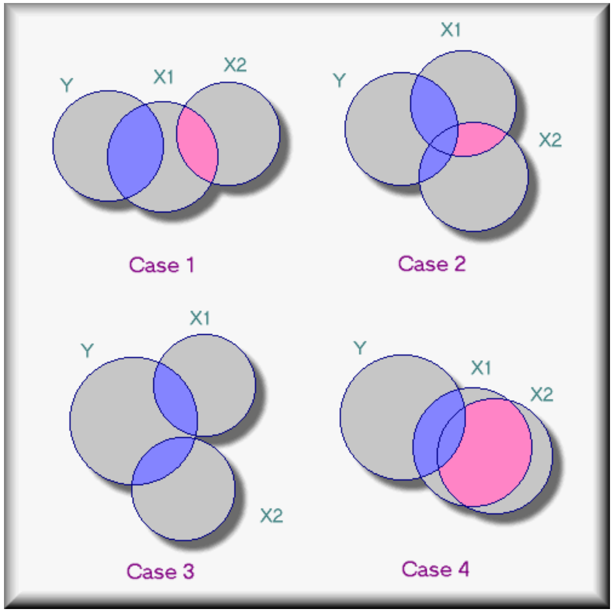
$$\begin{pmatrix}0 & 4 & 0\\ 2 & 0 & 0\\ 0 & 0 & -5\end{pmatrix} = \begin{pmatrix}0 & 1 & 0\\ 1 & 0 & 0\\ 0 & 0 & 1\end{pmatrix}\begin{pmatrix}4 & 0 & 0\\ 0 & 2 & 0\\ 0 & 0 & -5\end{pmatrix}$$





INDEPENDENCE AND CORRELATION





ICA: CONVOLUTIVE LINEAR MIXTURES

Mixing model

$$x(t) = A(t) * s(t)$$

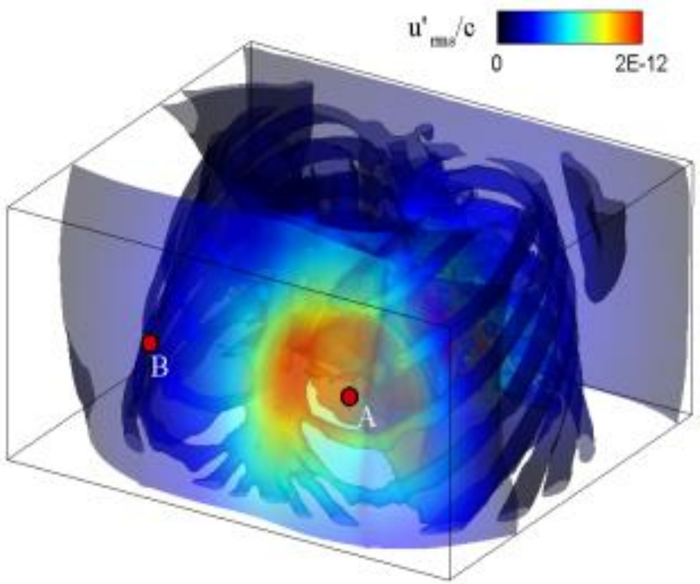
First theoretical results:

Let $x(t) = A(z)s(t)$, where $A(z)$ is an invertible matrix, whose entries are filters.

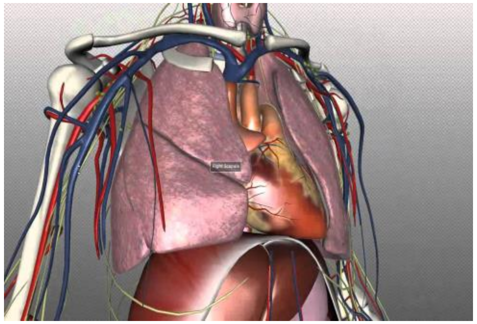
$Y(t) = B(z)x(t)$ is a random vector with mutually independent components if and only if $B(z)A(z) = D(z)\,P$

HEART SOUND PROPAGATION

http://www.youtube.com/watch?v=QIyBINP9QjU



Propagation effects



- The source of information's are correlated and bound together by physical, chemical controls and by communication phenomena existed on cardiac system.
- These mechanical waves propagate on the thorax, which is an heterogeneous medium and interference and distortion phenomenon's are present.
- The fonts may be mixed with each other, or with a time-delay version of itself and in the worst scenario it may be mixed with time-delay version of another waves, therefore in the stethoscope a mixing complex signal is recorded

CONVULOTION OPERATION

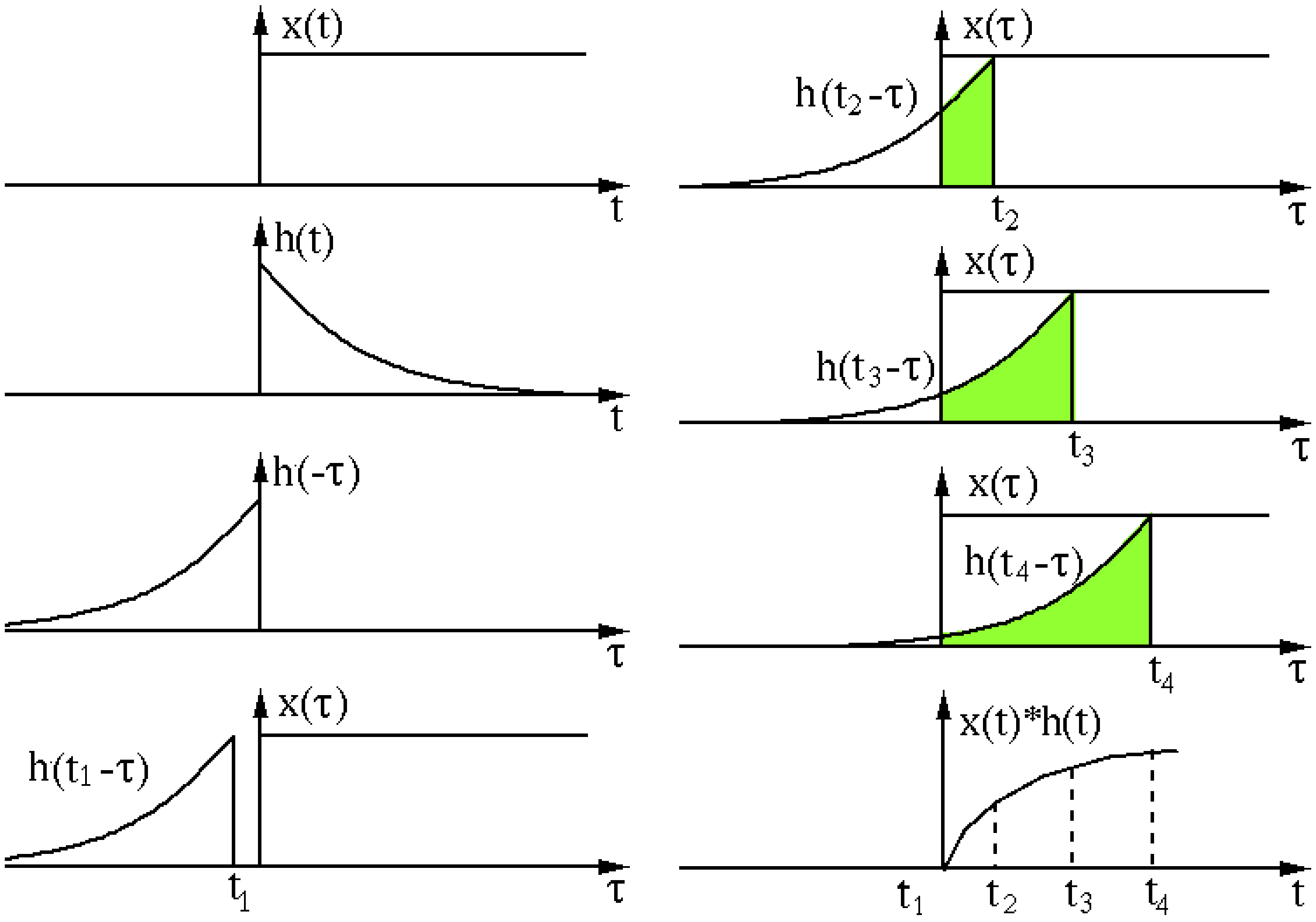
17-11-2014

- For any given *n*, how to obtain

$$g(n) = \sum_{k=-\infty}^{\infty} h(k) f(n-k)$$

  - Step 1: time reversal of either signal (e.g., *f(k)*$\rightarrow$*f(-k)*)
  - Step 2: shift *f(-k)* by n samples to obtain *f(n-k)*
  - Step 3: multiply *h(k)* and *f(n-k)* for each *k* and then take the summation over *k*

Convulotion Operation

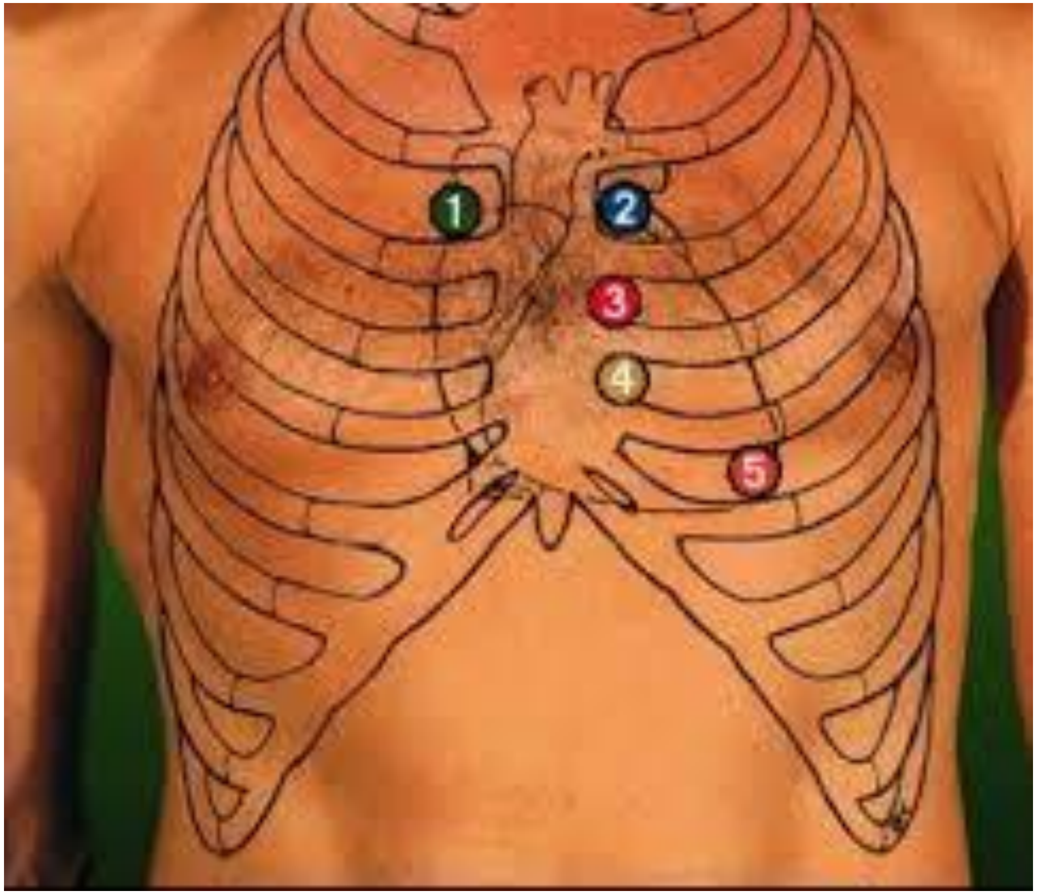


Blind or not Blind?

- Non blind: mixing nature is known, assuption on the sources
- Blind: non assumption is made about the channel (no information about the input)


first experiment with guide-horse failed
?
SKROENS)
SKRONS)
SMEK
CANARY PETE
Search: 06530345

Number of sources and observations



DETERMINED OR OVERDETERMINED LINEAR MIXTURES

- **Determined mixtures:**

Equal numbers of sources and sensors(mixtures) $K = P$

A is a regular matrix

- **Overdetermined mixtures**

More sensors (than sources) $K > P$

Solution if the mixing matrix is full rank (P)

Pre-processing with PCA(Principal Component Analysis)

UNDERDETERMINED MIXTURES

- More sources than sensors(mixtures) $P > k$
- Identification of A and source estimation are two distinct and tricky problems.
- If A is known (its inverse does not exist !), one cannot directly estimate s
- Without extra priors, infinite number of solutions.
- Possible solution for discrete or sparse sources.

Separation in noisy mixtures

- Noisy mixtures:
  $x(t) = As(t) + n(t)$

Where the noise n is independent of the sources s.

Noise has two main effects:

It leads to an error estimation of B.

If we estimate B perfectly $B = A^{-1}$ than:

$$y(t) = Bx(t) = s(t) + Bn(t)$$

Kullback-Leibler divergence

$$D(p,q) = \sum_x p(x)\log_2\left(\frac{p(x)}{q(x)}\right)$$

- $D(p,q)$ is a positive number except when p and q.

Drawbacks:

- Computation of the K.L divergence requires marginal and joint's distributions.

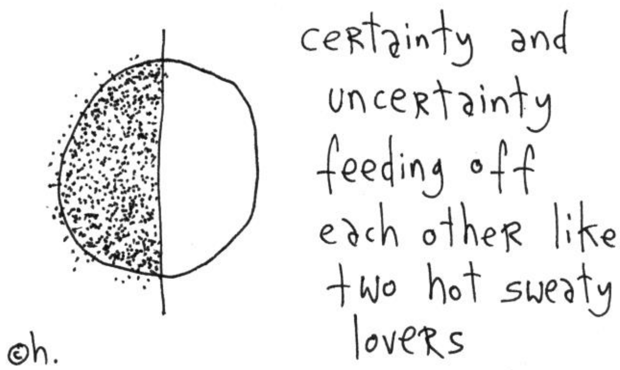
Advantages:

- Good independent measure

Mutual Information

- $r(x, y)$ is a joint p-q distribution.

$$I(X,Y) = \sum \sum r(x,y) \log_2 \left(\frac{r(x,y)}{p(x)q(y)} \right)$$



MUTUAL INFORMATION AND ENTROPY

- $I(X,Y)=H(Y)-H(Y/X)$
- $I(X,Y)=H(X)-H(X/Y)$
- $I(X,Y)=H(X)+H(Y)-H(X,Y)$
- $I(X,Y)=I(Y,X)$
- $I(X,X)=H(X)$

A TRICK FOR LINEAR MIXTURES

- In the linear determined case, with an invertible matrix A
- $I(Y) = \sum H(Y_i) - H(\boldsymbol{Y})$
- $\boldsymbol{Y} = \boldsymbol{B}\boldsymbol{X}$
- $I(Y) = \sum H(Y_i) - H(\boldsymbol{X}) - E[log|det\boldsymbol{B}|]$
- Consequence:
- $min_B\, I(Y) \leftrightarrow \sum H(Y_i) - H(\boldsymbol{X}) - E[log|det\boldsymbol{B}|]$
- Using this trick we avoid estimating joint entropy

MI MINIMIZATION AND SCORE FUNCTION

- For solving linear mixtures, one estimate a separating matrix, **B**, which minimizes $\boldsymbol{I}(\boldsymbol{y})$
- Derivative of MI with respect to **B** :
- $\frac{d(Y)}{dB} = -\sum E\left[\frac{-d\log p_{Y_i}(y_i)}{dy_i}\frac{dy_i}{dB}\right] - B^{-T}$

- MI minimization and HOS
- After some algebra

$$\frac{d(Y)}{dB} = 0;$$

We solve this equation system:

$$E\left[\frac{-d\log p_{Y_i}(y_i)}{dy_i}\ y_i\right] = 0$$

Definition: Independence

- Two functions independent if

  $$E\{h_1(y_1)h_2(y_2)\} = E\{h_1(y_1)\}\, E\{h_2(y_2)\}$$

  - If variables are independent, they are uncorrelated
- Uncorrelated variables
  - Defined: $E\{y_1 y_2\} = E\{y_1\}\, E\{y_2\} = 0$
  - Uncorrelation doesn’t equal independence
  - Ex: (0,1),(0,-1),(1,0),(-1,0)
  - $E\{y_1^2 y_2^2\} = 0 \neq \frac{1}{4} = E\{y_1^2\}\, E\{y_2^2\}$

Second Order Separation

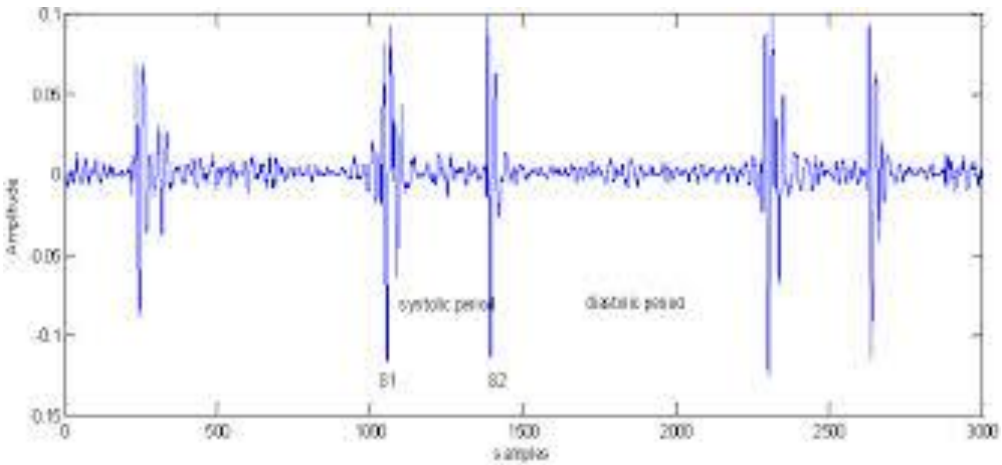
- For iid sources:

  - Impossible!!!

- For non iid Sources:

  -Colored Sources

  -Non-stationary sources



BASIC IDEA

- Compute separating matrix **B** which decorrelates simultaneously $y_i(t)$ **and** $y_j(t - \tau)$ for various τ **and** $\forall\, i, j$
- Equivalent to diagonalize simultaneously :

$E[y(t)y(t-\tau)^T]$, for at least two values of τ.

Joint Diagonalization

- Covariance Matrices of s: $R_s(\tau) = E[s(t)s^T(t-\tau)]$.

- Covariance Matrices of x:
  $R_x(\tau) = E[x(t)x^T(t-\tau)] = AR_s(\tau)A^T, \forall\tau$.

Can be simultaneously diagonalized by matrix B.

IDENTIFIABILITY THEOREM FOR COLORED SOURCES

- The mixing matrix **A** is identifiable from the second order statistics, iff the correlation sequences of all the sources are pairwise linear independent $\rho_i(1), \ldots \ldots, \rho_i(K) \neq \rho_j(1), \ldots \ldots, \rho_j(K) \; \forall i \neq j$
- Identifiability in the time domain can be transposed in the frequency domain:
- The mixing matrix **A** is identifiable from second order statistics , iff the sources have distinct spectra. Pairwise linear independent spectra.

CONSEQUENCES

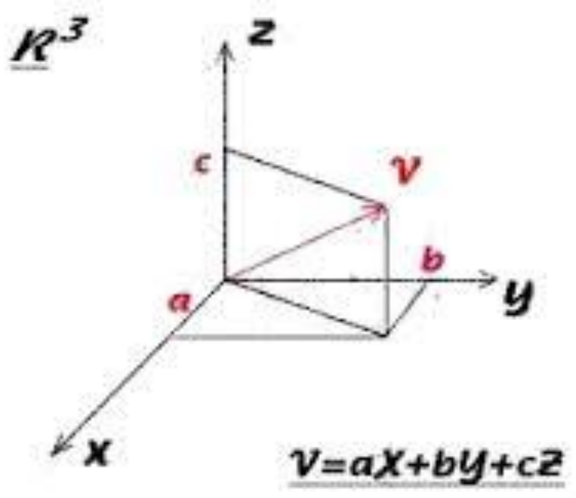
- Since separation is achieved using second order statistics (SOS). Gaussian sources can be separated.
- Since we just use (SOS), maximum likelihood approach can be developed assuming Gaussian Densities.

Multidimensional Independent Component Analysis

- Components are not assumed to be all mutually independent.
- The sources are divided into tuples.
- Inside of the same tuple, the sources are dependent. In different tuples, they are independent from the other components.

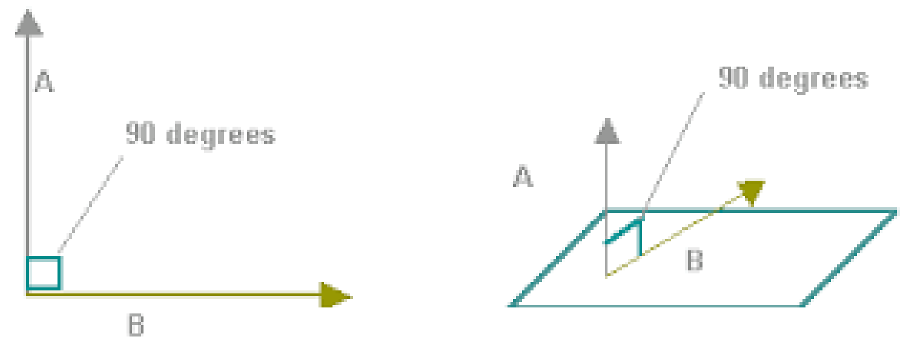
DEFINITION 1

- Let $E_1 \oplus \ldots \ldots \ldots . . \oplus E_c$ be c a linear subspace of $\Re^n$. They are said to be linearly independent if any vector **x**, can be uniquely decomposed :
- $\boldsymbol{x} = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{c}} \boldsymbol{x_i}$, with $\boldsymbol{x_i} \boldsymbol{\epsilon} \boldsymbol{E_i}$ for $1 < \mathrm{p} < \mathrm{c}$.
- In such cases $\boldsymbol{x_1} \ldots \ldots . . \boldsymbol{x_p}$ are linear components of $\boldsymbol{x}$ on the set $E_1, \ldots \ldots \ldots . . , E_c$



DEFINITION 2

- A random n- dimensional vector **x** admits of a MICA decomposition $\{x_1, \ldots\ldots, x_c\}$ in c components if it exists c linearly independent components subspace $E_1 \oplus \ldots\ldots\ldots\ldots \oplus E_c$ of $\Re^n$, on which linear components are statistically independent.



INDEPENDENT SUBSPACE ANALYSIS

- The explicit dependency between sources is modeled.
- Let $k, n \in N$ such that k divides n. We call an n-dimensional random vector **y** k-independent if the k-dimensional random vectors $(y_1 \ldots . y_k)^T, \ldots \ldots, (y_{n-k+1} \ldots . y_n)^T$ are mutually independent

MICA FOR MIBSS

- x= As where $A \in Gl(n, \mathbb{R})$ and s is a k-independent n-dimensional vector. Finding the indeterminacies of MICA then shows that A can be found except for k equivalence (separability), because if x= As and W is a demixing matrix such that **Wx** is k-independent, then $WA \sim_k I$ **so** $W^{-1} \sim_k A$ as desired.

$$\left[\begin{array}{c|c} A_1 & A_2 \\ \hline A_3 & A_4 \end{array}\right] \left[\begin{array}{c|c} B_1 & B_2 \\ \hline B_3 & B_4 \end{array}\right] = \left[\begin{array}{c|c} C_1 & C_2 \\ \hline C_3 & C_4 \end{array}\right]$$

VARIANCE DEPENDENT *BSS* MODEL

- Double-blind approach –> Sources are dependent through their variances and have a temporal correlation.
- In a topographic ICA this dependencies are estimated using a prefixed neighborhood relationship.

Variance-dependent Blind Separation

- Each source signal $s_i(t)$ is a product of non-negative activity level $v_i(t)$ and underlying i.i.d signal $z_i(t)$. This is $s_i(t)$ = $v_i(t)z_i(t)$. All the vectors are in $\Re^n$.
- In practice, the activity levels $v_i(t)$ are often dependent among different signals and each observed signal is expressed as:
- $x_i(t) = \sum_{j=1}^{n} a_{ij} v(t)_j z(t)_j, \qquad i = 1 \dots . n$

ASSUMPTIONS

- $z_i(t)$ have zero mean and unit variance for all i
- ***Z*** is mutually independent.
- $z_i(t)$ and $v_j(t)$ are mutually independent for all i, j, t**.**
- But $v_j(t)$ and $v_i(t)$ are mutually dependent over time.

Objective Function

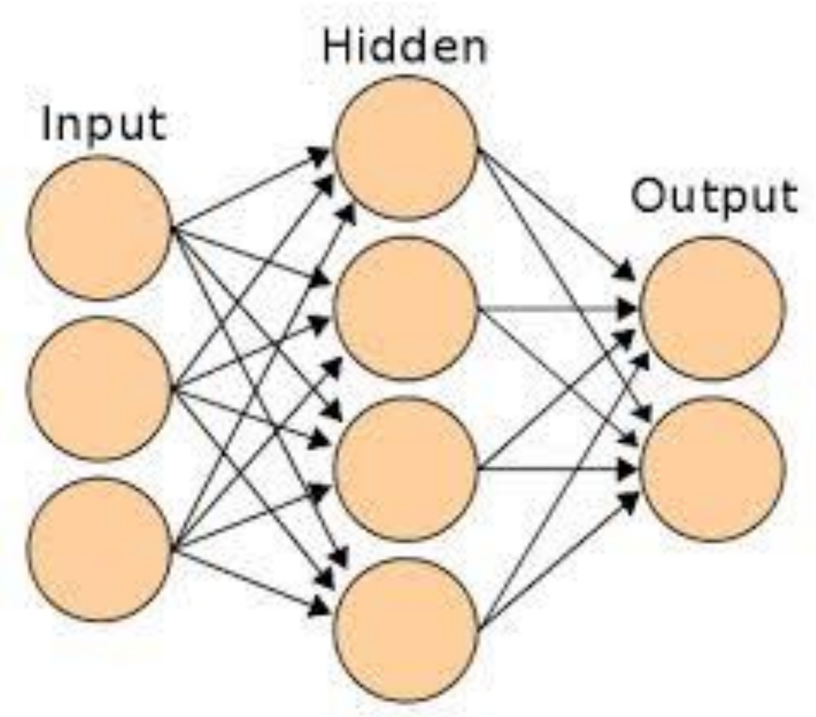
- Pre-processed with a spatial whitening filter
- J(w)= $\sum_{i,j}[cov(w^{T}{}_{i}\, z(t))]^2, [cov\big(j\, z(t-\Delta t)\big)]^2$
- Where $W(w_1, \ldots\ldots, w_n)^T$ is constrained to be orthogonal and lag time Δt not zero.
- Making the **K**:
  - $K_{i,j} = cov(s^2{}_i(t), s^2{}_j(t-\Delta t))$ has a full rank matrix.
  - He J is maximized when **WA** is a signed permutation matrix.

LOOKING TO THE SECOND HEART SOUND

Pratical Application

NEURAL NETWORK - INTRODUCTION

http://www.youtube.com/watch?v=gcK_5x2KsLA



Segmentation of the Second Heart Sound

WHY?

S2 split during the Respiratory cycles is an important information of the heart Hemodynamics.

- So What will we do ?
- Using Neural Networks for Blind Source Separation of Convolved Sources Based on Information Maximization Principles

Blind Source Separation

The Best Possible Clue to Separate A2 and P2 Components !!!

Bell derived a self-organizing learning algorithm which maximizes the information transferred throughout the network.

The non linearity in the transfer function is able to pick up higher-order moments of the input distributions and perform a redundancy reduction between units in the output representation.

What is the Point?

It can be used to separate out the mixtures of independent sources (blind separation) or reversing the effect of the unknown filter (blind deconvolution).

Maximum information is transferred when the slop part of the sigmoidal function is optimally lined up with high density parts of the input and this can be achieved in an adaptive manner, using stochastic gradient ascent rules.

BELL NEURAL NETWORK

HOW IT WORKS?

Maximum information is transferred when the slop part of the sigmoidal function is optimally lined up with high density parts of the input and this can be achieved in an adaptive manner, using stochastic gradient ascent rules.

Disadvantages :

- It only uses a single network layer and the optimal mappings discovered are constrained to be linear.
- It does no take into account time delays between the sensors
- It was not tested in a real noisy environment

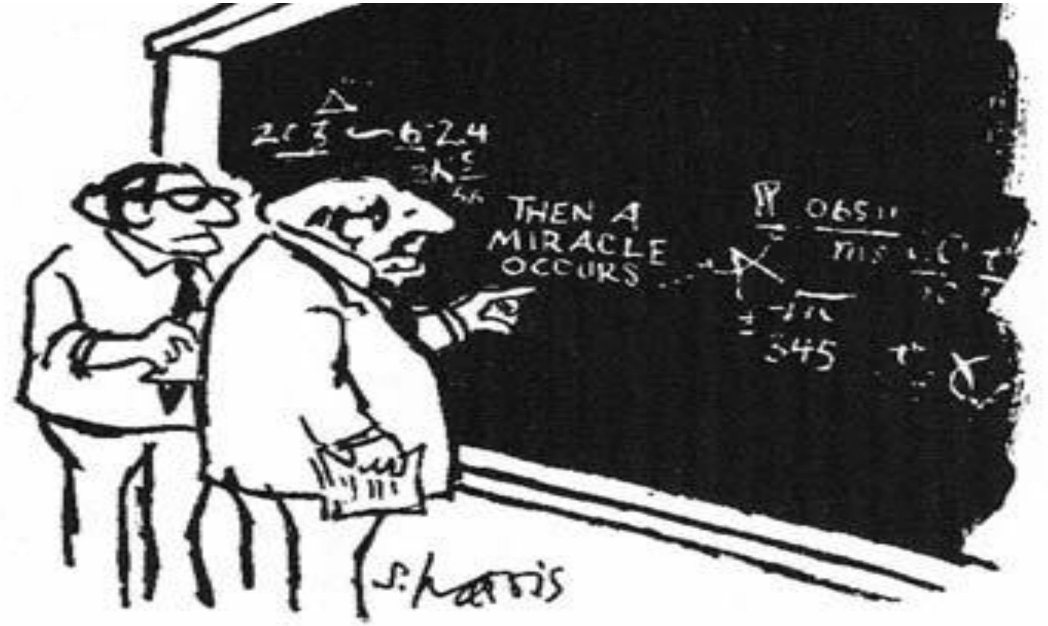
BUT !!

Torkkola extended for the cases where the sources may be delayed with respect to each other. He also derived the adaptation equations for the delays and weights in the network by maximizing in the information transferred through the network.

AND !!

- Amari developed a new on-line learning algorithm which minimizes a statistical dependency among outputs is derived for blind source separation of mixed signals

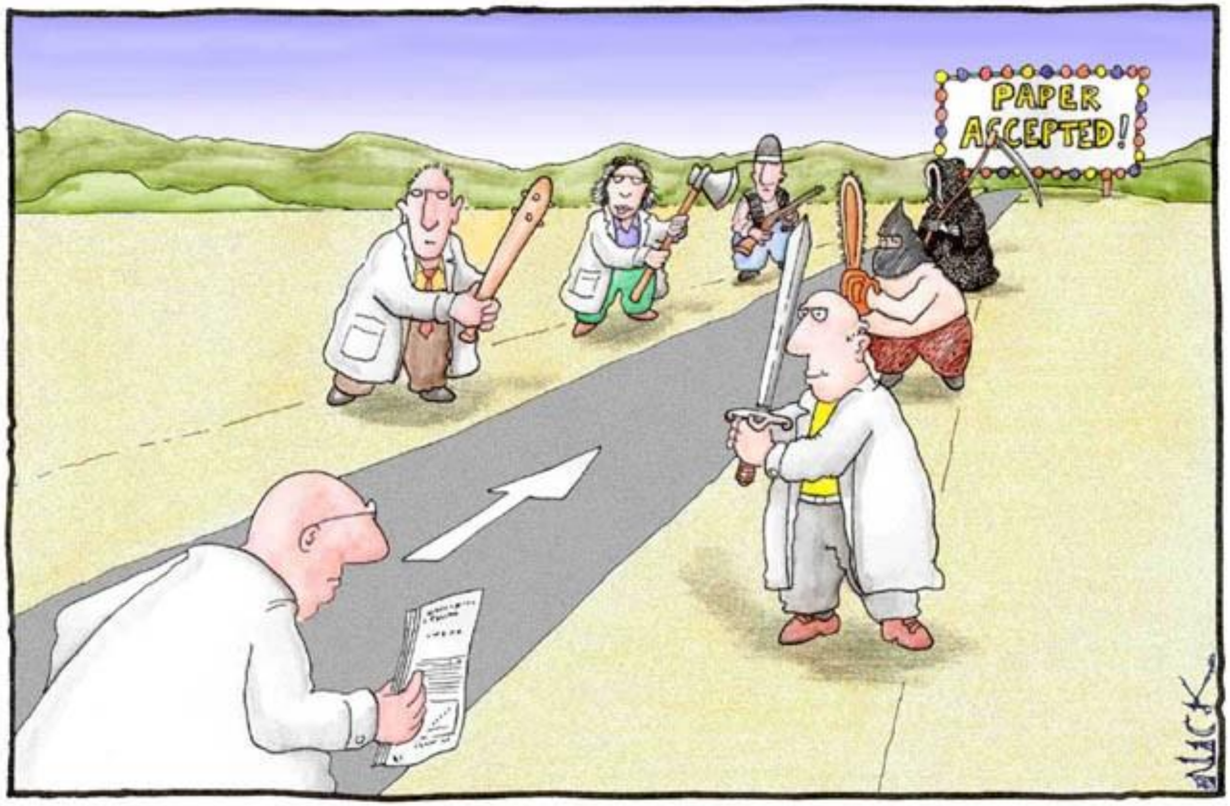
Gathering all these ideas...........
.... Maybe!!!!!



"I think you should be more explicit here in step two."

Thank You

QUESTIONS??



Most scientists regarded the new streamlined peer-review process as 'quite an improvement.'