# **General Blind Source Signal Separation**

# **Problem Statement**

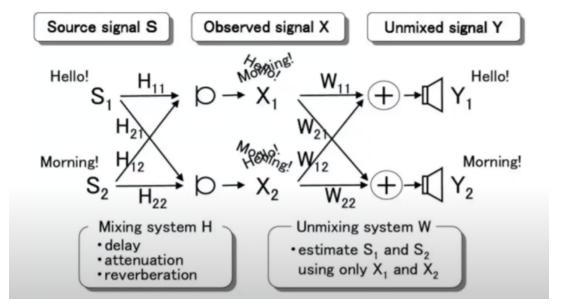
Find the separation of a set of source signals from a given set of mixed signals.

The mixed signals is represented as a column vector x;  $x \in \mathbb{R}^n$ ,  $n \in \mathbb{N}$ .

You have no information about how the mix happened between the sources, nor do you know any information about the source.

You can assume the following:

- The number of independent sources is equal to the number of mixtures (the number of independent sources is also n).
- Independent sources are non-gaussian signals and that they are mutually independent.



# **Encoding function**

we have n independent sources  $s_1(t)$   $s_2(t)$ ...  $s_n(t)$  represented as a vector

$$s(t) = [s_1(t) s_2(t)... s_n(t)]^T$$

 $A; A \in \mathbb{R}^{n \times n}$ , is called the mixing matrix, represents the mixture coefficients where  $-5.0 \le a_{ii} \le 5.0$  for  $1 \le i, j \le n$  and  $i, j \in \mathbb{N}$ .

$$x(t) = As(t)$$
,

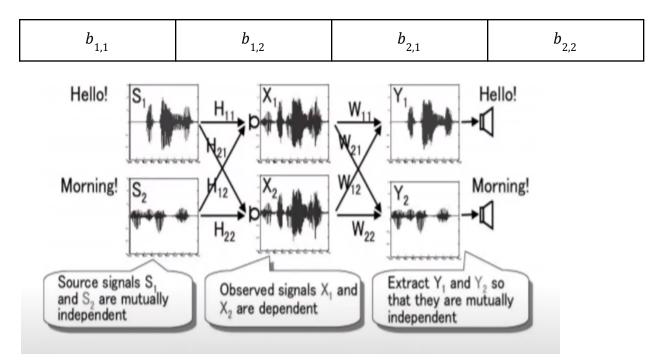
To find the source signals, we want to optimize the following equation,

$$y(t) = Bx(t),$$

$$y(t) = [y_1(t) y_2(t)... y_n(t)]^T$$

$$B \in R^{nxn}, -5.0 \le b_{ij} \le 5.0$$

B as a chromosome, we can just flatten the matrix to a one dimensional vector, where each gene correspond to an entry in the matrix B, if n=2 then a chromosome for B is



# **Selection method**

## Initial population

We choose the size of the population, let it be k, then we generate k random candidate solutions (chromosomes).

#### Selection

"using the helpful parts of biological evolution, and replacing the parts that might not work for us"

Tournament selection.

We choose the size of the tournament that is 20% of k, which is the size of the population, and round it to the nearest power of two.

We choose the probability p such that 0 of each selection, and distribute the probabilities for each position in the tournament to be chosen as follows,

$$p * ((1 - p)^{\alpha_i}); \alpha_i$$
 is the fitness for chromosome i

This keeps running until we have our population complete (number of selection = k), then the selected parents are passed to crossover and mutate.

#### Crossover

- Multiline crossover
- Multiline with random crossover

#### Mutation

We chose a mutation rate of 0.01, where we change a certain gene to a random value m;  $-5 \le m \le 5$ 

# **Fitness function**

"The nearer the individual to the solution of the optimization problem, the more fit is the individual"

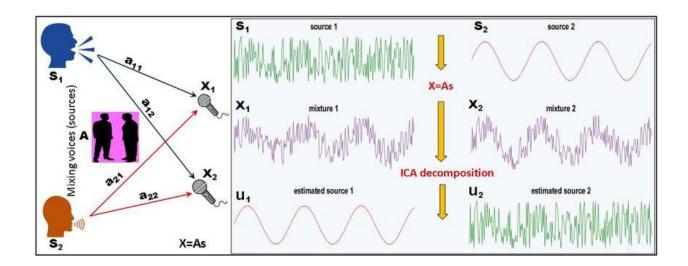
maximization of the kurt sum, minimize the mutual information

- Kurt is used to show the independency of the components of the source signals.
- Mutual information (MI) is used to show how much common information between two random variables X and Y.

"In optimization, it is more convenient to solve minimization problems. However, the opposite perspective would be valid, too."

let  $M \in \mathbb{R}^{n \times n}$ ,  $n \in \mathbb{N}$ , and it's entries are the  $MI(y_i, y_i)$ 

$$f(y) = \sum_{i=1}^{n} |kurt(y_i)| + \sum_{i=1, j=1, i!=j}^{n} 100e^{-10m_{ij}}, for all m_{ij} < 0.2$$



### Ref

- Medical Imaging Signals And Systems
- A Genetic Algorithm for Blind Source Separation Based on Independent Component Analysis
- Signal separation
- Cocktail party
- Independent component analysis
- Medical imaging
- A real-time blind source separation scheme and its application to reverberant and noisy acoustic environments
- Blind Signal Separation: Statistical Principles
- Dynamic Programming Algorithms for Computing Optimal Knockout Tournaments
- Independent component analysis: algorithms and applications
- What is mean by the non-gaussianity in the independent component analysis(ICA)?
- Independent Component Analysis (ICA) | by Shawhin Talebi
- A Short Introduction to ICA
- Projection pursuit