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Blind Separation of underwater sources using Signal Processing techniques and the Herault-Jutten model

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Abstract :
In underwater acoustics, we use a set of sensors (array) in order to have some knowledge on the environment. Usual signal processing tools for underwater acoustic signals require some geometric knowledge regarding the propagation and the data gathering system. The signals received by sensors are mixtures of different elementary sources. An optimal use of those sensors will be to isolate all the sources, without any a priori knowledge : this issue is called blind separation of sources. This paper present the different approaches (signal processing and neuromimetic) witch can be used. The advantages and disadvantages of the different methods will be summarised. Some results of the separation of underwater sources using the Herault-Jutten model will be presented.

1. Introduction

The Blind Separation of Sources problem arises from different fields such as astronomy, astrophysics, underwater acoustics, medical applications. According to the domain, one can focus on an object (star, ship, electrocardiogram wave, etc.) that produces some signals (optical, electromagnetic, acoustics signals, etc..)
In underwater acoustic, the signal received by sensors is a mixture of different elementary sources, filtered by the environment. For example, these different sources could be the signatures of vessels, the noise made by the environment, self-noise, etc.. The optimal use of the sensors will be to separate all these sources. This issue is called blind separation of sources because we do not have any a priori knowledge about these sources : the only hypothesis made is that they are statistically independent.
Different approaches can be used to solve this problem : signal processing (heuristic, analytic or tensorial) or neuromimetic approaches. This paper will give an over view of the different methods witch can be used.

2. Problem statments

The characterisation and linear filtering of data are based on quadratic criterion related to the notion of energy or interaction energy. This can be defined as second order classical methods [8].
Considering a multidimensional set of data, the main tool is the cross spectral matrix. Such approach is perfectly adapted to random gaussian data. Both, the analysis order and the gaussian property, allowed some useful analytic developments to investigate a situation. But this kind of approach and signal could not be used for all purposes. Some limitations exist as we will see shortly.

The sources path trough a transmission field and are received on a set of sensors. Using only the knowledge of the received signals (mixtures), one can try to characterise the initial sources.
The transmission field is supposed to be isotropic deterministic, to present a stationary property and furthermore to be linear. So the received signals can be considered as linear mixtures of the initial sources.
The most general linear mixtures are convolutive. We will only investigate here the special case of instantaneous mixtures. This corresponds to a memoryless system or a spectral analysis of a defined channel. The instantaneous case is general enough to understand the key points of the sources separation problem.

Let introduce some notations :
s_i (t) denoted the random signals index i produced by p sources, with t denoted the time index. The random nature of the signal is stated to stay coherent with the statistical tools used for the theoretical justification of the approach. Then deterministic signals can be also analysed.
$x_j(t)$ denoted the received signals index j. For simplification reasons, the number of sensors is equal to the sources one. Their is no big deal to come back to such situation as long as we got more sensors than sources. A Principal Decomposition Analysis will do the job.

The received signals and the sources can be related by the following relationship using matrix notations :

$$\underline{X}(t) = \underline{\underline{M}}\ \underline{S}(t) + \underline{N}(t) \qquad (1)$$

$\underline{X}$ is the Vector collection of the received signals x_j, $\underline{\underline{M}}$ denoted the mixture matrix, $\underline{S}$ denoted the vector collection of the sources s_i et $\underline{N}$ denoted an additional isotropic gaussian noise.

Then the sources separation problem can be stated as :

> The blind separation of sources consists on the procedure that estimates a set signals proportional to each sources ($\underline{S}$) using only the received signal ($\underline{X}$) and the statistical properties of the sources.

To perform the separation a characterisation criteria has to be defined to distinguish between the different sources.
The first possible hypothesis is the decorrelation properties of the sources [9].
This means that the sources cross-correlation matrix $\underline{S}\,\underline{S}^T$ is diagonal. Supposing that the sources present an unitary power, and that the noise can be neglected the cross-correlation matrix of the received signals is equal to :

$$\underline{XX}^T = \underline{\underline{MM}}^T \qquad (2)$$

The decorrelation hypothesis can hold of the examples above : the signals coming from two stars have physically no relationship, nor the acoustic noise of two ship engines are synchronised.
The decorrelation condition of the sources is a basis for the sources separation methods developed H. Mermoz, using the spectral matrix [10]. Then a lot of array processing methods were also introduced [12].
The first methods based on spectral matrix are "heuristic" developments and were justified by a "Maximum Likelihood Principle"(ML) later on [1]. However, as stated by H. Mermoz, the ML approach confirms the fact that the spectral matrix information has to be mixed with other physical knowledge to perform the separation.
An illustration of this limitation can be seen by doing a spectral decomposition of the mixture matrix $\underline{\underline{M}}$.
This matrix can be written as :

$$\underline{\underline{M}} = \underline{\underline{V}}.\underline{\underline{\Delta}}.\underline{\underline{\Pi}} \qquad (3)$$

where $\underline{\underline{V}}$ and $\underline{\underline{\Pi}}$ are unitary matrices and $\underline{\underline{\Delta}}$ a diagonal matrix.

The correlation matrix of the received signal defined in (2) can be written as:

$$\underline{XX}^T = \underline{\underline{V}}.\underline{\underline{\Delta}}.\underline{\underline{\Pi}}\,\underline{\underline{\Pi}}^T\underline{\underline{\Delta}}^T\,\underline{\underline{V}}^T \qquad (5)$$

The $\underline{\underline{\Pi}}$ Matrix product disappears because of the unitary property. So the correlation is only related to the $\underline{\underline{V}}$ and $\underline{\underline{\Delta}}$:

$$\underline{XX}^T = \underline{\underline{V}}\,\underline{\underline{\Delta}}\,\underline{\underline{\Delta}}^T\underline{\underline{V}}^T \qquad (6)$$

The $\underline{\underline{\Pi}}$ Matrix could not be determined using only the second order analysis. The output result is, for this case, a set of uncorrelated data also an infinite number of solutions according to this criteria, can be obtained by multiplying one solution by any unitary matrix.
Fortunately for those methods, complementary physical hypothesis are available to constraint the system so the separation can be reached. In the sonar field a plane wave hypothesis allowed such result. If the field behave as an isotropic one (at list near the sensors) and the sources are placed at an infinite distance, the signal received by a linear array can be separated.

But in other cases all this convenient hypothesis are not available.
An other existing solution that does not need further hypothesis : its principle is to make a better use of the independence properties of the sources. The sources are then supposed to be statistically independent random processes.
This statistical property is usually stated for the spectral matrix based methods but only verified up to the second order. The independence is only partially used.
The second usual hypothesis is the gaussian like models of the sources that allowed nice theoretical analytical developments. In this case the second order analysis is optimum regarding the gaussian character of the sources.

The basic hypothesis are then :
- the sources are statistically independent processes;
- the sources are non gaussian processes.

The last hypothesis is mandatory to assure the existence of new information into higher order statistics. In fact the independence property assure that all the cross statistics are null whatever analysis order is used.
Using this property, one can show that enough equation can be written to determined all the free parameters of the system.

Different solutions have been proposed using this principle :
• the Heuristic solution proposed by P. Ruiz et J.L. Lacoume has shown the real possibility of sources separation using higher order criteria on independent sources [13];
• the Analytic approach using directly the relationships of the linear model through the structure of higher order statistics. This solution proposed by P. Comon leads to the notion of Independent Component Analysis [4];
• A Tensorial solution based on particular structure and transformation of the fourth order statistics, done by J-F Cardoso, ends up with the notion of eigen structure of tensor that allowed strait forward extension of MUSIC like algorithms [3];
• the Neuromimetic approach by C. Jutten et J. Herault generates higher order statistic properties through non linear function and leads to simple and efficient algorithms [11], [7].

3. The neuromimetic solution

To solve the issue of BLIND SEPARATION OF SOURCES, two French researchers, J. Hérault and C. Jutten, propose a neuromimetic solution. The structure of Hérault-Jutten network rests on inhibitive recurrent connections [6].

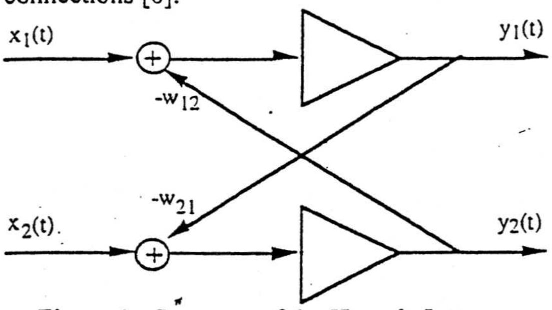

Figure 1 : Structure of the Herault-Jutten network

This structure is justified by the following idea : if sources are statistically independent, it is possible to extract one of them by weighted subtractions of the others. Then the outputs will be then proportional to the sources.

The learning is unsupervised : the weights w_{ki} are changed adaptively in order to make the outputs statistically independent.

$$\Delta w_{ki} = a.f(y_k).g(y_i - <y_i>) \qquad (7)$$

$<y_i>$: average estimation of the neurone i output
f and g : non linear odd functions
a : adaptation gain of the neural network.

It is easy to demonstrate, that in the case of linear mixtures :

$$x_1(t) = a_{11}\ s_1(t) + a_{12}\ s_2(t)$$
$$x_2(t) = a_{21}\ s_1(t) + a_{22}\ s_2(t) \qquad (8)$$

the two sources $s_1(t)$ and $s_2(t)$ will be separated if the weights reach the optimal values :

$$w_{12} = \frac{a_{11}}{a_{21}} \quad et \quad w_{21} = \frac{a_{22}}{a_{12}}. \qquad (9)$$

We use the Herault-Jutten model to separate linear mixtures of simulated complex underwater signals.
The simulations are realistic approaches of the underwater sources as the sound made by merchant ships, submarines, flow noise, etc.. They were made with a sophisticated synthesiser, SYTER, under control of an audio expert.
By merging simulated signals, it is possible to obtain different mixtures and to evaluate the results (separation of the signals) obtained with the neural network. The experiments were made using the MatLab software.

Figure 2 shows an example of a separation of a two underwater sounds : a submarine and an hydrodynamic source.

The mixtures are linear and the coefficients equal to :
$a_{11} = 0.8$; $a_{12} = 1$; $a_{21} = 1$; $a_{22} = 0.7$

After 4000 iterations, the weights reach the optimal values : $w_{11} = 0.8$ and $w_{22} = 0.7$

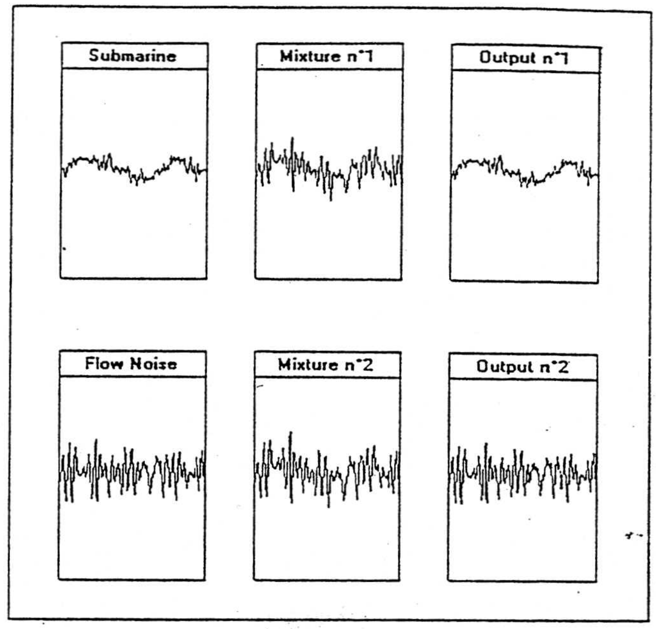

Figure 2 : Separation of underwater sources

The neuromimetic solution is very interesting in the field of separation of underwater sources. Its main advantages are :

- the model can be extended to n sources without any difficulty since the number of sensors is greater than or equal to the number of sources, which does not raise any trouble for linear arrays considering the large number of hydrophones used ;

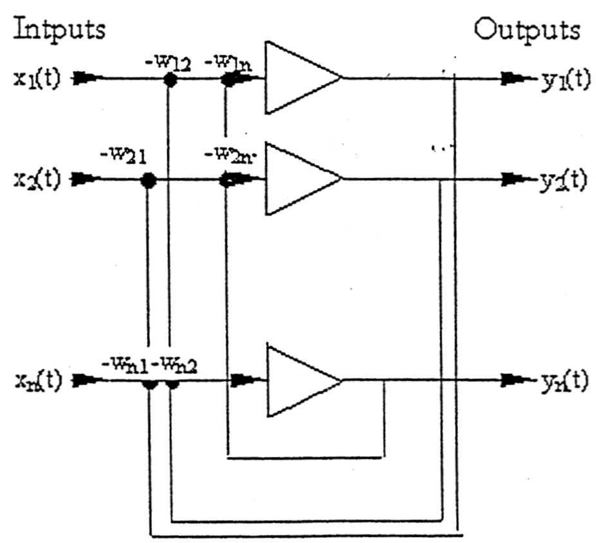

Figure 3 : Neural network architecture for the separation of n sources by n neurones

- this neuromimetic algorithm is adaptive : it is possible to pursue the separation if the mixtures change;

• this algorithm is very simple : hardware could be implemented directly on the array or at the output of hydrophones.

4. Conclusion

The neuromimetic solution, using a cross statistic criteria, gives a simple way to process the separation and to follow the unstationnarity of the environment. The results obtained are promising. The low computation cost and the rapid convergent have to be underlined. An extension of the technique to the convolutive mixtures of sources can be considered [11]. Nevertheless this criteria does not shear the properties of contrast type criteria [4], [5] and are more sensitive to estimation problems. The cases of impulsive sources has to be taken carefully.
Isolating each source would give an optimal use of this array. For example, relevant sources, such as submarine or vessels signals, will be isolated ; or unwanted sources, such as hydrodynamic noises, could be eliminated. This challenging technique can be applied in various fields such as : self-noise reduction (unwanted sources could be eliminated), classification (useful sources would be separated).

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