NEURAL NETWORKS FOR BLIND SOURCES SEPARATION OF STROMBOLI EXPLOSION QUAKES

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ABSTRACT

Independent Component Analysis (ICA) is used to analyze the seismic signals produced by explosions of Stromboli Volcano. It has been experimentally proved that it is possible to extract the most significant components from seismometer recorders. In particular, the signal, generally thought as generated by the source, is corresponding to the higher power spectrum, isolated by our analysis.

1. INTRODUCTION

Stromboli is a volcanic island of Aeolian arc in the Tyrrhenian sea. The volcano rises about 924 m above sea level and most of the products are ejected from the craters placed on a terrace 700 m above sea level. This volcano is characterized by a periodic activity: there is an explosion about every ten minutes. The recorded signals are characterized by explosion quakes superimposed on a background continuous signal, the sustained tremor. Due to a rapid loss of coherence of the wave field and to the absence of clear impulses, it is very difficult to study these signals using classical methods. Spectral analyses have shown the presence of marked peaks, that have been connected to the source mechanism. In particular, it has been put in evidence the bimodal nature of these spectra, showing that there is a release of energy into two bands of frequency, the first one in a band between 1 and 3 Hz, the second one between 3 and 5 Hz. The 1-3 Hz band is connected to the existence of body waves, and the second one is connected to the presence of surface waves generated by the superficial part of the source and by scattering sources distributed in the whole island. A main goal of geophysical studies is to separate these excitations, i.e. the part of signal directly connected to the source from those due to the presence of scatters [1]. We use ICA to make this separation and we show that ICA is suitable to our aim.

The selected explosion quakes are taken from seismic signals recorded in April 1992 with small arrays of electromagnetic seismometers, by *United States Geological Survay* (USGS), University of Aquila and Vesuvian Observatory. The recorded signals represent ground velocity. Three arrays were settled near Stromboli Volcano 1.5 km far from craters. In particular, we examinate the data recorded with the linear array settled by Aquila University. This array is composed of 15 stations equipped with 125 Hz sampled three-component seismometers. It is placed along a line extending in the crater direction, with about N18S degree, so that the N-S component of the array has recorded the radial component of wavefield. We use, for our analysis, this radial component that recovers the most significant trace of source [2]. The typical time lenght of one of this seismic signals is about 23 seconds. In the first few seconds, the signal is highly correlated, the azimuth distribution is peaked on 18-19 degrees indicating that the wavefield effectively comes from craters. The wavefield associated to this component is composed of body waves in the first few seconds, then of Rayleigh waves for other few seconds, and finally of some other waves produced by scattering sources [3].

2. INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis (ICA) [8],[9] is an unsupervised technique which tries to represent the data in terms of statistically independent variables. ICA has lately drawn a lot of attention both in unsupervised neural learning and statistical signal processing.

In particular, efficient new neural learning algorithms [10][11] have been introduced for ICA and applied to the closely related blind sources separation (BSS).

We consider the standard linear data model used in ICA and BSS:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) = \sum_{i=1}^{m} s_i(t)\mathbf{a}_i \tag{1}$$

Here the components $s_i(t)$, $i = 1, \ldots, m$, of the column vectors $\mathbf{s}(t)$ are the m unknown, mutually statistically independent components (or source signals) at time t. For semplicity, they are assumed to be zero mean and stationary. The components of the n-dimensional data vector $\mathbf{x}(t)$ are some linear mixtures of these independent components or sources. The $n \times m$ mixing matrix $\mathbf{A}$ is an unknown full rank constant matrix with $n \geq m$. At most one of the independent components $s_i(t)$ is allowed to be Gaussian. For learning the ICA expansion (1), an $m \times n$ inverse or separating matrix $\mathbf{W}(t)$ is updated so that the m-vector

$$\mathbf{y}(t) = \mathbf{W}(t)\mathbf{x}(t) \tag{2}$$

becomes an estimate $\mathbf{y}(t) = \hat{\mathbf{s}}(t)$ of the independent components. Since the mixture model of equation 1 has permutation and scale invariance, then the estimate $\hat{s}_i(t)$ of the i^{th} independent component may appear in any component $y_i(t)$ and the amplitudes are scaled to have a unit variance. The basis vectors $\mathbf{a}_i$ of ICA can be estimated as column vectors of the pseudoinverse $\mathbf{W}^T(\mathbf{W}\mathbf{W}^T)^{-1}$ of $\mathbf{W}$.

In several ICA or BSS algorithms, the data vectors $\mathbf{x}(t)$ are preprocessed by whitening them: $\mathbf{v}(t) = \mathbf{V}(t)\mathbf{x}(t)$. Here $\mathbf{v}(t)$ denotes the whitened vector satisfying $E[\mathbf{v}(t)] = \mathbf{0}$, $E[\mathbf{v}(t)\mathbf{v}(t)^T] = \mathbf{I}$, where $\mathbf{I}$ is the unit matrix, and $\mathbf{V}$ is an $m \times n$ whitening matrix. Thus in this approach the total separating matrix is $\mathbf{W}(t)\mathbf{V}(t)$.

In the following we shall use the fixed-point algorithm [13] devoloped by Hyvärinen to perform the BSS. In a previous work [12] X. Giannakopoulos, J. Karhunen and E. Oja compared the performance of the most used neural or adaptive algorithms designed for ICA and BSS. The algorithms are applied to three different real-word data set and the most important conclusion of their comparison are the robustness and the efficiency of fixed-point algorithms. One iteration of generalized fixed-point algorithm for finding a row vector $\mathbf{w}_i^T$ of the separating matrix $\mathbf{W}$ is [13]

$$\begin{aligned} \mathbf{w}^* &= E[\mathbf{v}g(\mathbf{w}_i^T\mathbf{v})] - E[g'(\mathbf{w}_i^T\mathbf{v})]\mathbf{w}_i \\ \mathbf{w}_i &= \mathbf{w}_i^*/\|\mathbf{w}_i^*\| \end{aligned} \tag{3}$$

where $g(\cdot)$ is suitable nonlinearity, typically $g(y) = \tanh(y)$, and $g'(y)$ is its derivate with respect to y.

3. SEISMIC DATA ANALYSIS

Figure 1 shows an example of explosion-quake and figure 2 its power spectrum.

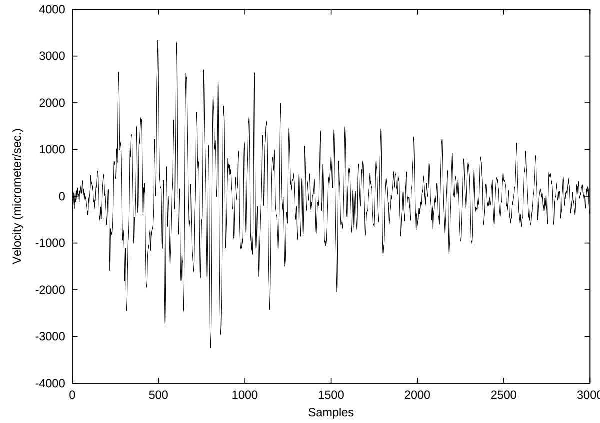

Figure 1: An example of explosion quake recorded at Stromboli

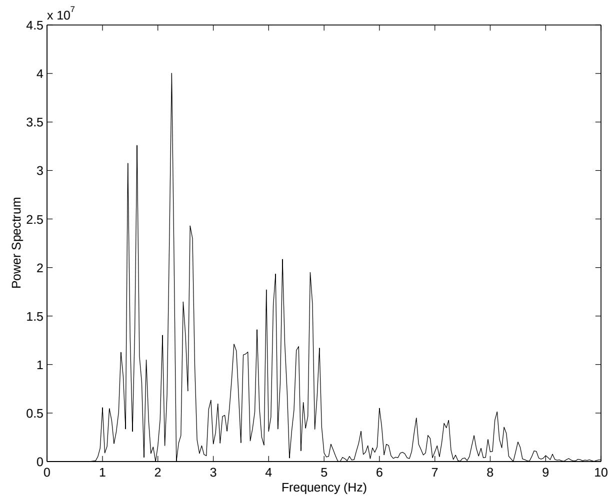

Figure 2: Power Spectrum of the signal plotted in figure 1

As written in the introduction, the spectrum reveals a complex dynamics with several components. The data are the same explosion quake recorded at different stations along a line, as shown in figure 3. We know the apparent velocity of the first impulse from a previous work [2]. Then, we can estimate the arrival time of the first impulse at each station and we can synchronize all the traces with respect to the first recording. In this way we can consider the recordings like an istantaneous mixture of source signals, scattering radiations and environment noise, and so we can apply the standard linear ICA.

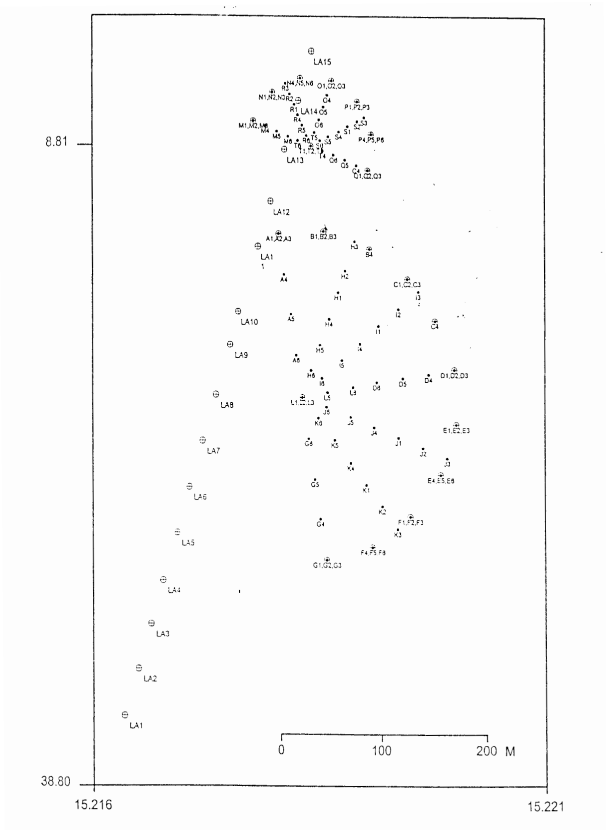

Figure 3: Array position. The data, used in the experiment, are recorded by the stations LA1-LA15

Firstly, we analyze the eigenvalues of the correlation matrix (see figure 4) so that we can determine the information held in each signal. One of the aim of this paper is to determine if ICA must be applied before or after a smoothing preprocessing. Hence we separate our experiment into two steps:

1. we smooth the signals with a non-linear noise reduction then we apply ICA

2. we firstly apply the ICA and then we smooth the signals with a non-linear denoising.

We use a standard technique of nonlinear noise reduction to eliminate the noise and the presence of a dinamycal system with an attractor dimension higher than that we take into account to model the explosion quake. We prefer to use this method rather then standard linear filtering: in fact the signals derived from non linear sources can exhibit genuine broad band spectrum and there is not any justification to identify any part of the spectrum as noise as it would be using linear filters. The non-linear denoising takes into account the fact that deterministic signals form smeared-out lower

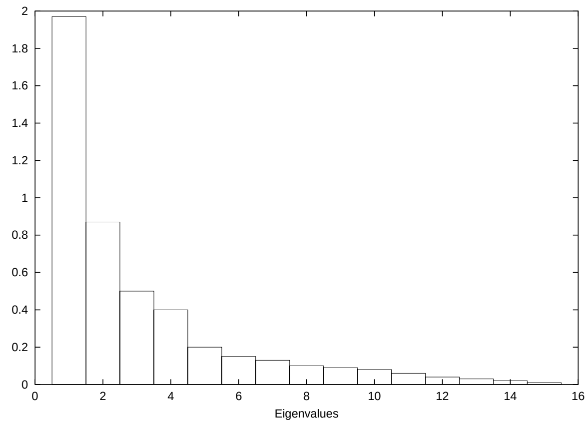

Figure 4: Eigenvalues of correlation matrix

dimensional manifolds: as a consequence the denoising identifies such manifold structure and projects the signal into this manifold to reduce the noise [4].

The non-linear denoising requires the knowledge of some characteristic parameters: the time lag, the embedding dimension, and the manifold dimension. We use a method proposed in [5] to determine the phase space parameters. A suitable time lag that describes system dynamics is selected searching the first minimum of the *Average Mutual Information* (AMI) criterion [6]. This can be seen as a generalization of the linear autocorrelation function. Then, we use the *False Nearest Neighbours* algorithm [7] to find how many samples are necessary to unfold the unknown phase space. We obtain 0.08 s for time lag and six for the embedding dimension. In a previous work [1] it has been proved that the source of explosion quake can be modelled by a self sustained oscillator whose attractor dimension is two. Hence we project the data into a bidimensional space to eliminate the high dimensional dynamics.

4. EXPERIMENTAL RESULTS

On the basis of the above described preprocessing we extract six independent components from the explosion quake signal. We made several experiments changing the sequence of application of differents techniques. We conclude that the denoising step eliminates relevant information from the signals. As we can see in figures 5 and 6 a good separation is not obtained, the interpretation of each component is very difficult and the power spectra of denoising data are very close to the spectra of the original ones. On the other hand, as we can see in figure 7, if we apply ICA before filtering, the six components retain all the information, so that the algorithm performs an optimal separation. In fact, four indipendent components with a different spectral contents appear (signal 1,2,4 and 6). We conclude that, in the denoising step, the lost information is relevant to model the system dinamics.

Now we remark that ICA algorithm is like a filter in the time domain. If anyone compares the spectral contents of the four cited components with the original spectrum of figure 2, he can recognize the most significant peaks. The sixth component, that has a well marked peak about 1Hz, contains the revelant part of signal: namely the sixth component holds more than 40% of signal information. This component is the direct source signal, confirming the results of [1].

5. CONCLUSIONS AND FUTURE RESEARCH

In this paper we have shown that ICA is a suitable technique to be applied to the analysis of Stromboli explosion quakes. In fact, we can draw the following conclusions: the ICA must be applied before denoising and other smoothing techniques that can eliminate relevant information contained in the signals; we extract the significant part of signal using six components; the application of denoising to the components so obtained clearly selects a deterministic signal that can be associated to the sources.

While here we analysize the signal recorded along the radial direction from the source, in the future research we think to extend our analysis to other directions (vertical and transverse directions). In this way we can identify the physical origin of the other components put in evidence by ICA. Futhermore, we want to analyze, with ICA, signals produced by other seismic sources. In particular it could be of interest to study tectonic signals, composed of waves propagating with different velocities.

6. REFERENCES

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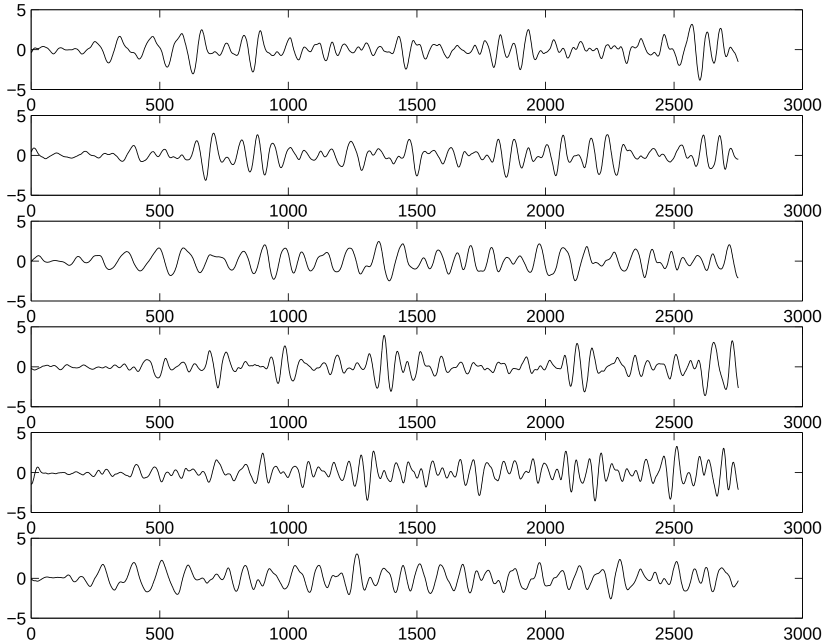

Figure 5: Signal obtained if we filter the data before we apply ICA

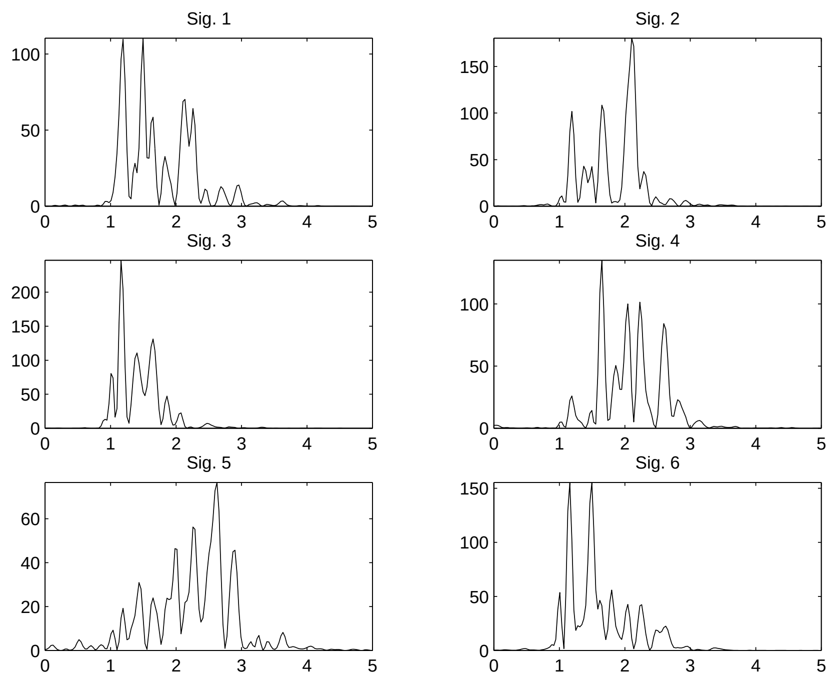

Figure 6: Power Spectra of each signal if we filter the data before we apply ICA

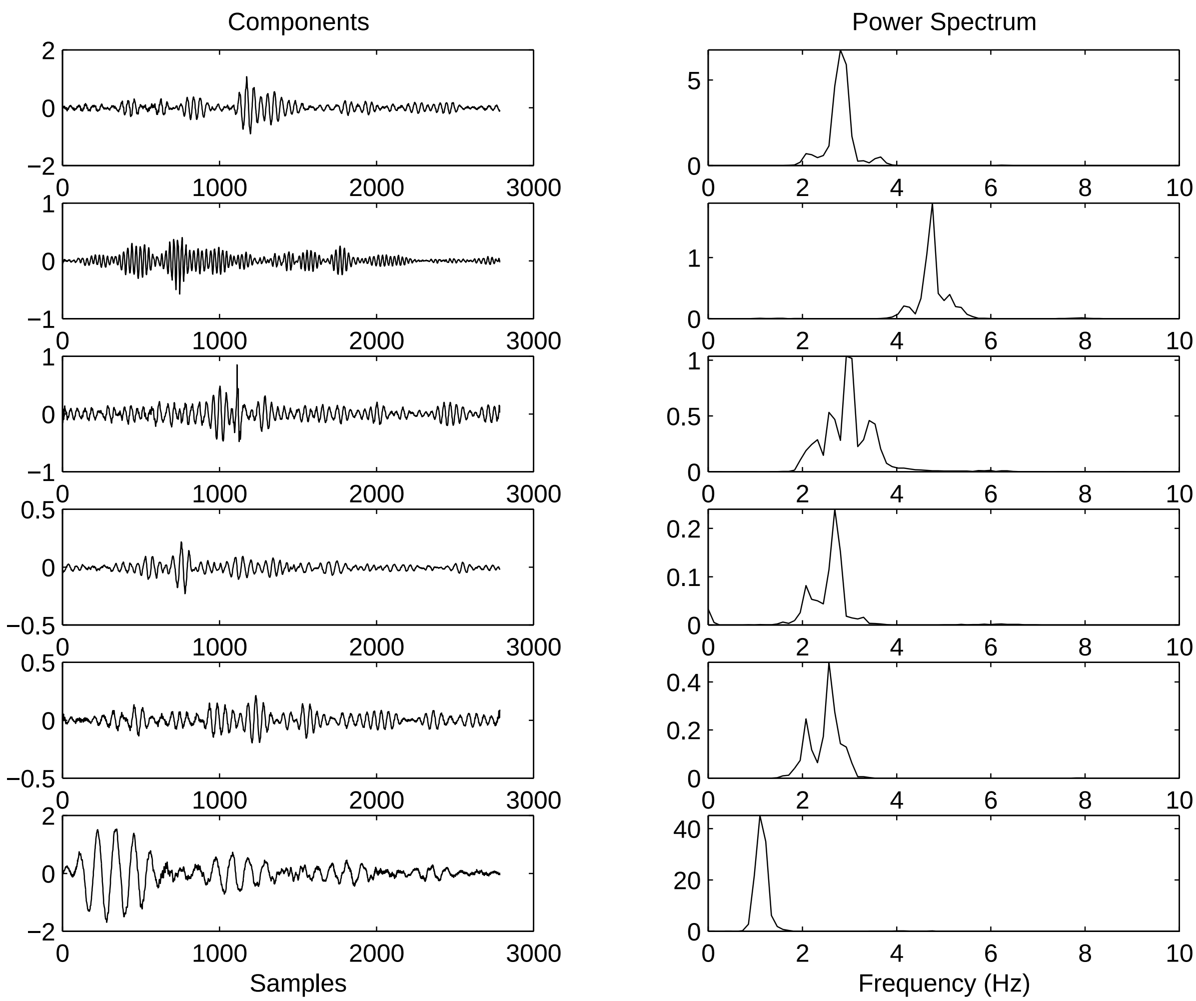

Figure 7: Independent components and their Power Spectra