INFRASOUND SIGNAL SEPARATION USING INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT

An important element of monitoring compliance of the Comprehensive Nuclear-Test-Ban Treaty (CTBT) is an infrasound network. For reliable monitoring, it is important to distinguish between nuclear explosions and other sources of infrasound. This will require signal (event) classification after a detection is made. We have demonstrated the feasibility of using neural networks to classify various infrasonic events. However, classification of these events can be made more reliably with enhanced quality of the recorded infrasonic signals. One means of improving the quality of the infrasound signals is to remove background noise. This can be carried out by performing signal separation using Independent Component Analysis (ICA). ICA can be thought of as an extension of Principal Component Analysis (PCA). Using ICA, noise, and other events that are not of concern, can be removed from the signal of interest. This is not a *filtering* process, but rather a technique that actually *separates* out the background noise from the signal of interest, even if the signals have overlapping spectra. Therefore, not only is the signal of interest *recovered*, but so is the background noise. The higher fidelity signal of interest (compared to any one sensor channel signal from the infrasound array before separation) can be presented to an event classifier (e.g., a neural network), and the background noise can also be further scrutinized.

We show two examples of infrasound signal separation using ICA. The ICA is performed using a neural network approach, i.e., an unsupervised nonlinear PCA subspace learning rule. The first example involves artificially mixing three different infrasonic signals from three separate events using a random mixing matrix, these mixed signals are then used to recover the original event signals. The second example is in the true spirit of ICA, i.e., the separation is performed blindly. From four channels of an infrasound array, these four inputs are used in the ICA to separate two signals, i.e., one "signal" the other "noise." The mixing matrix is not known, however, the separated *signal* of interest is shown to be the infrasound signal of a volcano eruption, and the separated *noise* is shown to contain characteristics of a microbarom signal. Moreover, in spite of overlapping spectra between the output signals of the ICA, separation of the signals is possible.

Key Words: Infrasound, independent component analysis, signal separation, neural network, nonlinear principal component analysis, overlapping spectra.

for $j = 1, 2, \cdots, h$, the elements a_{ij} are assumed to be not known, and $n_j(k)$ is additive measurement noise. We can now define the following, $x(k) = [x_1(k) \;\; x_2(k) \;\; \cdots \;\; x_h(k)]^T$, $x(k) \in \Re^{hx1}$, $s(k) = [s_1(k) \;\; s_2(k) \;\; \cdots \;\; s_q(k)]^T$, $s(k) \in \Re^{qx1}$ (the *source vector* consisting of the q independent components), and $A = [a_1 \;\; a_2 \;\; \cdots \;\; a_q]$, $A \in \Re^{hxq}$ (the *mixing matrix*), where the column vectors of A are the *basis vectors* of the ICA expansion. Equation (2) can now be written in vector-matrix form as

$$x(k) = As(k) + n(k) = \sum_{i=1}^{q} s_i(k) a_i + n(k) \tag{3}$$

referred to as the ICA expansion. We will assume the mixing matrix A contains at least as many rows as columns ($h \geq q$), and it has full column rank, i.e., $\rho(A) = q$ (i.e., the mixtures of the source signals are all different).

Independent Component Analysis Using Neural Networks

This discussion pertaining to the neural network approach for blind source separation using ICA follows the presentation by Karhunen *et al.* [10]. Figure 1 shows the basic neural architecture to perform the separation of source signals (i.e., estimate the independent components), and estimate the basis vectors of the ICA expansion, [i.e., estimate the column vectors of the mixing matrix A in (3)].

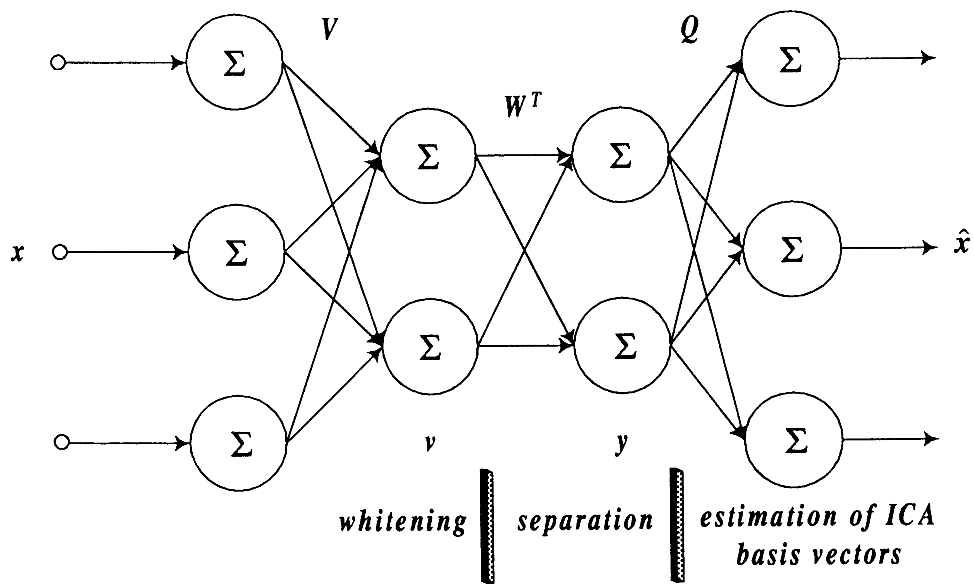

Figure 1. The ICA network. The three layers perform whitening, separation, and estimation of the basis vectors. The weight matrices that are necessary to determine are V, W^T, and Q.

Prewhitening Process

The whitening process that proceeds the separation step (i.e., prewhitening) is a critical procedure. This process normalizes the variances of the observed signals to unity. In general, separation algorithms that use prewhitened inputs often have better stability properties and converge faster. However, whitening the data can make the separation problem more difficult if the mixing matrix A is ill-conditioned or if some of the source signals are relatively *weak* compared to the other signals [11, 12]. The input vectors $x(k)$ are whitened by applying the transformation

$$v(k) = Vx(k) \tag{4}$$

adaptive separation algorithms. However, it is sufficient to use the kurtosis (fourth-order cumulant) of the data. Another class of separation methods involves using neural networks to perform the separation of the source signals [12]. In Fig. 1, the second stage of the architecture is responsible for the separation of the whitened signals $\boldsymbol{v}$. The linear separation transformation is given by

$$y(k) = \boldsymbol{W}^T \boldsymbol{v}(k) \tag{11}$$

where $\boldsymbol{W} \in \Re^{q \times q}$ ($\boldsymbol{W}^T \boldsymbol{W} = \boldsymbol{I}_q$) is the separation matrix. Thus the separated signals are the outputs of the second stage, i.e., $\hat{s}(k) = y(k)$. An interesting observation is once the source signal $s(k)$ has been estimated, this means that the pseudo-inverse of $\boldsymbol{A}$, i.e., $\boldsymbol{A}^+$, must have been also "blindly" determined [refer to (3)].

One very straightforward neural learning method to determine the separation matrix is based on the nonlinear PCA subspace learning rule [14-16] given by

$$\boldsymbol{W}(k+1) = \boldsymbol{W}(k) + \mu(k)[\boldsymbol{v}(k) - \boldsymbol{W}(k) g\{\boldsymbol{y}(k)\}] g\{\boldsymbol{y}^T(k)\} \tag{12}$$

where $\boldsymbol{v}(k)$ is the prewhitened input vector given in (4), and the function $g(\bullet)$ is a suitably chosen nonlinear function usually selected to be odd in order to ensure stability and for separation purposes. It is recommended that the learning rate parameter $\mu(k)$ be adjusted according to the adaptive scheme given in (9), with $\boldsymbol{v}(k)$ replaced by $\boldsymbol{y}(k)$. Also, for good convergence, it is best to select the initial weight matrix $\boldsymbol{W}(0)$ to have as columns a set of orthonormal vectors. Typically, the nonlinear function $g(\bullet)$ is chosen as

$$g(t) = \beta \tanh(t / \beta) \tag{13}$$

where $g(t) = \frac{df(t)}{dt}$ and $f(t) = \beta^2 \ln[\cosh(t / \beta)]$, the logistic function. This is not an arbitrary choice for the nonlinearity in the learning rule of (12). It is motivated by the fact that when determining the ICA expansion *higher-order statistics* are needed. This can be seen by observing another neural learning rule to perform separation of unknown signals. This learning rule is called the *bigradient algorithm* [10, 17, 18] given by

$$\boldsymbol{W}(k+1) = \boldsymbol{W}(k) + \mu(k)\boldsymbol{v}(k) g[\boldsymbol{y}^T(k)] + \gamma(k)\boldsymbol{W}(k)[\boldsymbol{I} - \boldsymbol{W}^T(k)\boldsymbol{W}(k)] \tag{14}$$

where $\gamma(k)$ is another *gain* parameter, typically about 0.5 or one. This is a stochastic gradient algorithm that maximizes or minimizes the performance criterion

$$J(\boldsymbol{W}) = \sum_{i=1}^{q} \mathrm{E}\{f(y_i)\} \tag{15}$$

under the constraint that the weight matrix $\boldsymbol{W}$ must be orthonormal. The orthonormal constraint in (15) is realized in the learning rule in (14) in an additive manner. With the appropriate function $f(\bullet)$ in (15), the performance criterion would involve the sum of the fourth-order statistics (fourth-order cumulants) of the outputs, i.e., the *kurtosis* [8]. Therefore, the criterion would be either *minimized* for sources with a *negative kurtosis* and *maximized* for sources with a *positive kurtosis*. Source signals that have a *negative kurtosis* are often called *sub-Gaussian* signals and sources that have a *positive kurtosis* are referred to as *super-Gaussian* signals. In (15) the expectation operator would be dropped because we only consider instantaneous values. We now write the logistic function $f(t) = \ln[\cosh(t)]$ (for $\beta = 1$) in terms of a Taylor series expansion

$$f(t) = \ln[\cosh(t)] = t^2/2 - t^4/12 + t^6/45 - \cdots \tag{16}$$

The second-order term $t^2/2$ is on the average constant due to the whitening. The nonlinearity would then be given by $g(t) = \frac{df(t)}{dt} = \tanh(t) = t - t^3/3 + 2t^5/15 - \cdots$, and the cubic term will be dominating (an odd function) if the data are prewhitened.

separated signals with respect to the actual source signals are almost perfect. The negative correlation coefficient indicates that a 180° phase shift has occurred in the output of the ICA separation process.

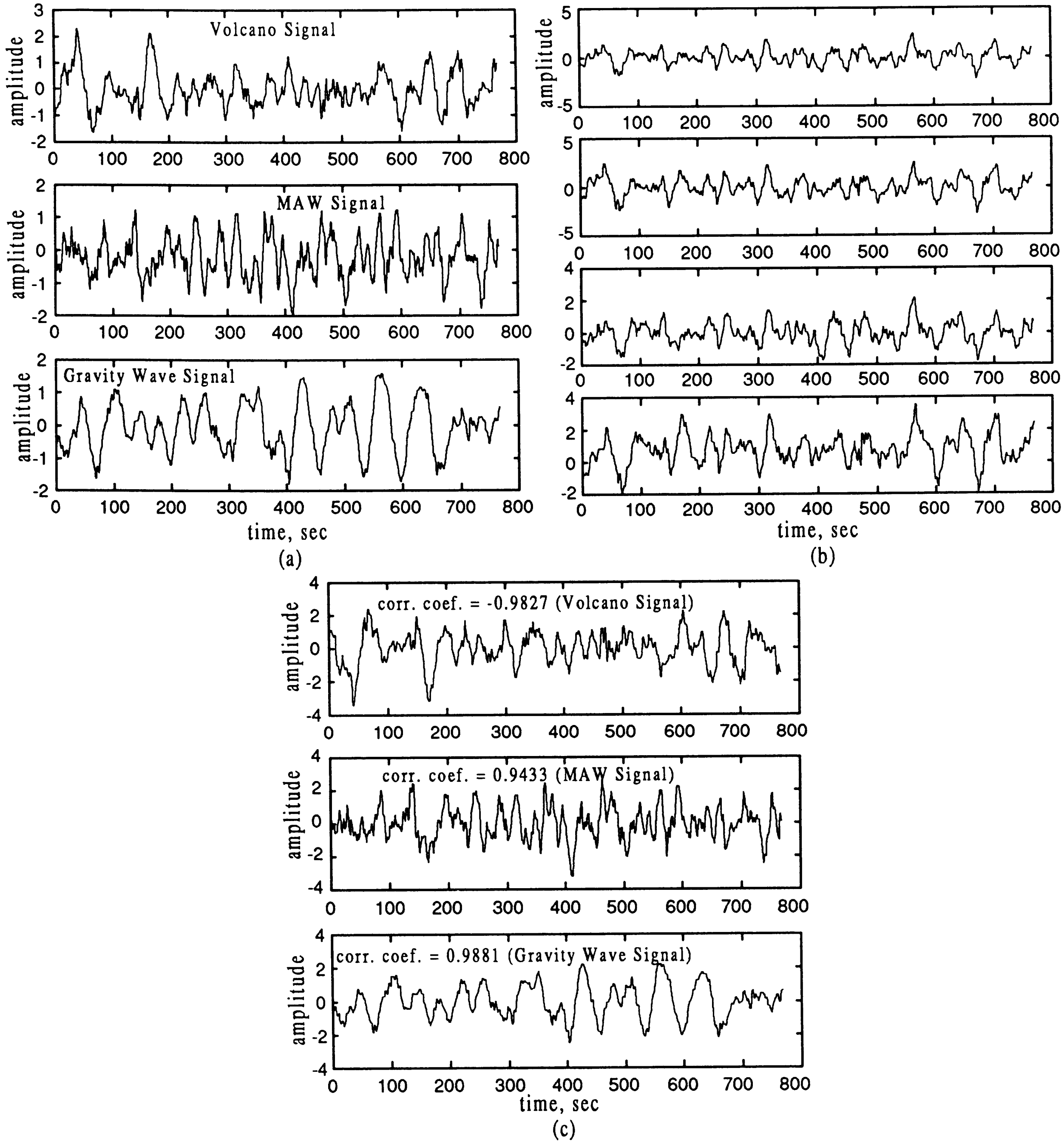

Figure 2. (a) Three original infrasonic source signals. (b) "Observed" mixed infrasound signals. (c) Separated infrasonic source signals using the nonlinear PCA subspace learning rule.

Simulation 2

The second example involves processing four infrasound signals from a large volcano eruption in Galunggung, Java in 1982. The signals analyzed were recorded from a single station, 4-sensor (F-array), infrasound array in Windless Bight, Antarctica. Fig. 3(a) shows the four recorded signals after beamforming [5] is applied to time align the signals to a common reference in the sensor array. The nominal sampling frequency is 1 Hz, and 590 time samples were retained from each signal record for analysis. It is assumed that the number of source signals is

ICA separated signal. Specifically, in the 0.1 to 0.2 Hz region there are two spectral peaks in both PSDs. Probably more profound is the observation made when comparing the bottom graph in Fig. 5(b) for the first separated signal, to the top graph in Fig. 6(c) for the second separated signal. Upon first glance when comparing these two spectra, they appear to be almost the same. However, when they are rescaled, shown in the top graph in Fig. 6(b) for the first separated signal, and the top graph in Fig. 6(d) for the second separated signal, the differences in the spectra can be seen. In fact, the correlation coefficient computed between the two time-domain signals is very low, specifically, 1.7992×10^{-4}. But more importantly is the overlapping spectra that exists between the two signals in the frequency range from 0.01 Hz to 0.02 Hz. In spite of this spectral overlap, ICA can separate the signals.

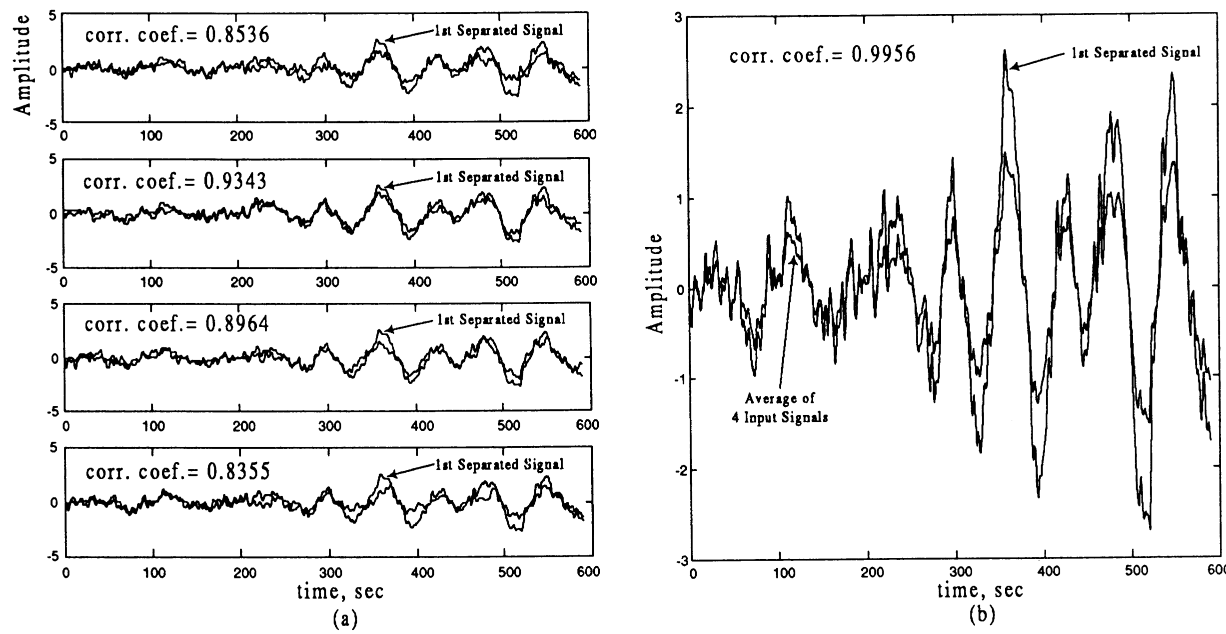

Figure 4. (a) First ICA separated signal superimposed on the four input signals. (b) First ICA separated signal superimposed on the average of the four input signals.

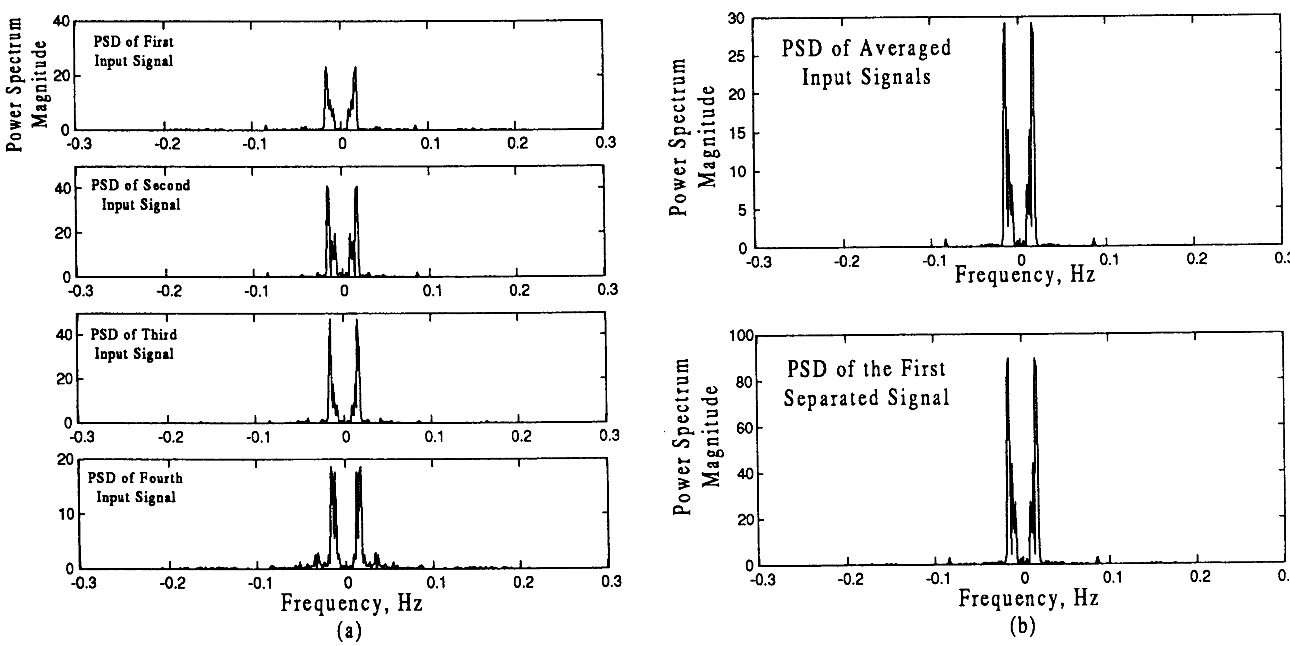

Figure 5. (a) PSD of the four ICA input signals. (b) Top Graph: PSD of the average of the four ICA input signals, and Bottom Graph: PSD of the first ICA separated signal.

the ICA was able to separate the signals. Further research in this area will involve investigating other infrasound recordings from the historical database [19, 20] for other types of events. When enough separated signals are generated for different infrasound events, this data set will be used to train and test a neural network classifier.

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