ELECTROMAGNETIC ENVIRONMETAL POLLUTION MONITORING: SOURCE LOCALIZATION BY THE INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT

The aim of this paper is to present an electromagnetic source localization technique based on independent component analysis (ICA). Two ICA algorithms known from the literature, allowing to process complex-valued signals, are used to estimate the mixing operator from electromagnetic data; as the mixing operator contains important information about the source complex structure and about the electromagnetic field propagation phenomena, by properly interpreting the results given by the ICA algorithm it is possible to develop a blind source localization procedure. Performing such procedure is the first step in electromagnetic environmental pollution monitoring.

1. INTRODUCTION

The continual growth of the telecommunication industry, with special emphasis to cellular phone systems and radio-TV broadcasting systems, has caused the alerting of the public opinion and of the governments about the electromagnetic pollution phenomena. In fact, the increasing number of electromagnetic emitters and the need of covering wider territorial areas have caused the spatial density of radiated fields to constantly increase, so that many countries have cautionary fixed by law the limits of allowed local high-frequency electrical and magnetic fields intensity.

The existence of such limits imposes the development of suitable procedures, allowing to measure the intensity of the fields in a given location, in order to verify if the constraints are fulfilled. In case of violation, however, the global information about the total measured field does not suffice to react in the proper way: It is in fact necessary to individuate the set of emission-stations insisting on the volume under observation, in order to plan a reduction of emitted field intensity for each station.

The first step consists in the electromagnetic sources localization. The scenario that the operations may be envisaged in, is that the sources may be far away from the area where the measures are taken, or may be hidden to the view: In both cases their locations are unknown; also, the spectra of the emitted signals might not necessarily be narrow-band, thus standard harmonic analysis does not necessarily help; moreover, the measurement station employed in the check might not be endowed with an antenna-array, but a low-cost single antenna might be available, which can be easily moved in many locations, thus standard localization techniques relying on spatial coherence of wavefronts would not be useful.

In this scenario, and under mild hypotheses about the kind of propagation and on the mid-term stationarity of the sources, a blind separation technique based on the independent component analysis (ICA) may be envisaged in order to blindly recover the source signals and, as an useful by-product, to locate the sources themselves.

In fact, the classical ICA techniques aimed at recovering the source signals from their mixtures [4, 5, 9], while only recently the attention has been turned to the physical meaning of the mixing operators, which may reveal important information about the geometry of the sources and the signal propagation models. Two pervasive contributions in this field have been given by Knuth [10] and Rowe [12], who designed specific algorithms for estimating the model parameters, which appear buried in the observed data, based on Bayesian and MAP inference algorithms.

These studies are also related to neurological electromagnetic source localization by EEG and fMRI data processing. Some contributions in this field have been given for instance in [8, 11, 13].

The aim of this paper is to present an application of the ICA technique to blind separation of signals emitted by antennas, and to interpret the geometrical information hidden in the mixing model in order to retrieve the source locations. It is worth noting that the signals involved are complex-valued, therefore the ICA algorithms should be able to train complex-weighted neural networks [4, 7].

2. BLIND SOURCE SEPARATION AND LOCALIZATION

In complex-valued blind source separation problem, a mixture of independent source signals is supposed to be observed:

$$\mathbf{x}(t) = \mathbf{P}^H \mathbf{s}(t) + \mathbf{n}(t) \ , \tag{1}$$

where $\mathbf{x}(t)$ is the observed R-dimensional random vector-signal, $\mathbf{P}$ is a constant complex-valued full-rank $R \times E$ mixing matrix, $\mathbf{s}(t)$ is the vector-stream containing the E source signals to be separated, and $\mathbf{n}(t)$ denotes the additive disturbance; the superscript 'H' denotes Hermitian transpose. Usually the number of observations exced the number of true sources, thus $R \geq E$. The only hypotheses made on the unknown sources are: (a) each $s_i(t)$ is an independent identically distributed stationary random process; (b) the $s_i(t)$ are statistically independent at any time; (c) at most one among the source signals is allowed to be Gaussian.

For separating out the linearly mixed independent sources, we use a neural network trained in order to make each neuron respond with signals as mutually independent as possible. Prior to be fed to the network, the observed signals are pre-processed in order to remove as much noise as possible and to reduce the redundancy in the observations, namely, to shrink the R-dimensional observation vector-stream $\mathbf{x}(t)$ into a reduced-size E-dimensional vector-stream $\tilde{\mathbf{x}}(t)$.

The separating network may thus be supposed to have E inputs and E outputs, and is described by the relationship:

$$\mathbf{y}(t) = \mathbf{W}^H(t)\tilde{\mathbf{x}}(t) \ , \tag{2}$$

where $\tilde{\mathbf{x}}$ is the network input vector, $\mathbf{y}$ denotes the output vector and $\mathbf{W}$ is the complex-valued weight-matrix. As the mixing model is linear, a linear separating structure is effective, thus the output $\mathbf{y}(t)$ in (2) is taken as a noisy estimate of the true source stream $\mathbf{s}(t)$.

In the present paper we suppose the sources to be antennas, and the receivers to be electromagnetic sensors. We further suppose the propagation to be cylindrical and both the sources and sensors radiation diagram to be hysotropic with good faith. In this case, each source E_i is described by a pair of coordinates (ξ_i^E, η_i^E), $i = 1, ..., E$, and each receiver R_i is described by (ξ_i^R, η_i^R), $i = 1, ..., R$.

In the present case the mixing matrix $\mathbf{P}$ has the physical meaning of a *propagator*, namely it describes the electromagnetic propagation in the air. For this reason, the (r, c)th entry of the propagation matrix $\mathbf{P}$ is described by the phasor:

$$P_{rc} = \frac{1}{D_{rc}} \exp[-j\gamma D_{rc}] \ , \tag{3}$$

$$D_{rc} = \sqrt{(\xi_r^E - \xi_c^R)^2 + (\eta_r^E - \eta_c^R)^2} \ , \tag{4}$$

where γ denotes the constant of propagation. Each phasor accounts for the loss of the wave-energy and of phase-rotation during propagation. This representation may be validated by computing the amplitude of the far-field electrical-field emitted by a dipolar antenna, an example of which is shown in the Figure 1: It confirms the goodness of the supposed propagation law.

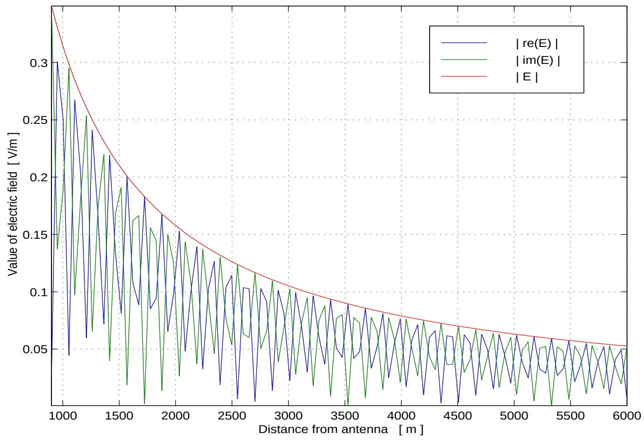

Fig. 1. Electrical field of a long dipolar antenna (far-field).

The central topic in ICA is to design an algorithm for training the neural network (i.e. to learn the connection matrix $\mathbf{W}$) in order to make the output signal of the network as independent as possible, and several algorithms are at present available.

In the present context we need an algorithm that exhibits good estimation precision regardless of the computational burden (in fact, the signal processing operations may be performed off-line), and that allows complex-valued signals handling. For these reasons, we chose to employ the complex fixed-point algorithm (CFP) [1] and the JADE algorithm [2], in order to compare their performances in this problem.

3. INTERPRETATION OF THE ESTIMATED PROPAGATION MODEL

Let us suppose the observed data pre-processing has been performed by a linear neural network decsribed by $\tilde{\mathbf{x}}(t) = \mathbf{V}^H\mathbf{x}(t)$ with $\mathbf{V}$ fixed on the basis of available data secondorder statistics decomposition, namely the reduction matrix has form $\mathbf{V}^H = \mathbf{D}^{-1}\mathbf{U}^H$ (the meaning of the matrices $\mathbf{D}$ and $\mathbf{U}$, and the algorithm for computing them, are explained in [2]). After training, the mixing operator may be estimated on the basis of the learnt quantities by the relationship:

$$\hat{\mathbf{P}}^H = \mathbf{UDW}\ . \tag{5}$$

In the hypothesis that the effect of additive noise has been made sufficiently small by the pre-processing operations, the relationship between the estimated mixing operator and the true propagator is $\hat{\mathbf{P}} = \mathbf{QP}$, where the new matrix $\mathbf{Q}$ is quasi-diagonal, in the sense that is has (approximately) only one entry per row different from zero [3]. In practice, this means that the propagator may be recovered up to arbitrary row permutation and scaling.

Let us restrict only to the module of the propagator entries, and let us evaluate the effect of the introduced distortion. By properly renumbering (re-labeling) the sources and sensors, it can be written:

$$|\hat{\mathbf{P}}| = \begin{bmatrix} k_1/D_{11} & k_1/D_{12} & k_1/D_{13} & \cdots \\ k_2/D_{21} & k_2/D_{22} & k_2/D_{23} & \cdots \\ \vdots & & & \end{bmatrix}\ ,$$

where the constants k_i take into account both the unknown signals powers and the unknown scaling factors in $\mathbf{Q}$, and the distances D_{rc} are also unknown.

The dependence on the unknown k_i may now be easily eliminated by normalizing each row about its first element, which makes available the ratios $\rho_{rc} \stackrel{\text{def}}{=} D_{r1}/D_{rc}$. If $R \geq 3$, we can approximately locate each source by triangularization. Moreover, the redundancy provided by the measures when $R \geq E$ allows adding robustness to the estimate of the position of the emitters; in practice, for each emitters we have 2 unknowns and $R-1$ equations, which form an overdeterminate set of non-linear equations in the two unknown; the solutions may thus be determined by a (robust) least-square-error (LSE) procedure.

As we may arbitrarily choose the locations of the measurement points, in order to simplify the following mathematical analysis we suppose the measures are taken along a straight line (the η axis of the reference system), at a distance of Y meters one from another; by convention we thus take $\xi_i^R = 0$; the origin of the reference system coincides to the 1st receiver position; the Figure 2 further clarifies the notation used.

The equations describing the geometrical relationships among the emitters and the receivers are:

$$D_{er}^2 = \xi_e^2 + \eta_e^2 + (r-1)^2Y^2 - 2(r-1)Y\eta_e\ ;$$

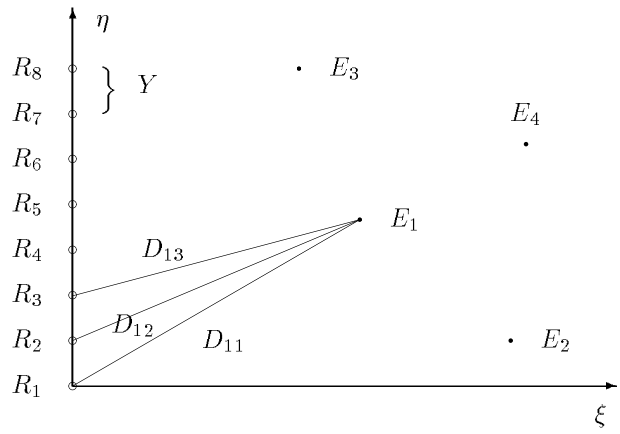

Fig. 2. Graphical description of the problem geometry and of the notation used.

in particular, for $r = 1$ we have $D_{e1}^2 = \xi_e^2 + \eta_e^2$. On the other hand, we know that $D_{e1}^2 = \rho_{er}^2 D_{er}^2$, thus we ultimately arrive at the set of non-linear equations:

$$(1-\rho_{er}^2)(\xi_e^2+\eta_e^2) = \rho_{er}^2[(r-1)^2Y^2 - 2(r-1)Y\eta_e]\ ,$$

for $r = 2,\ 3,\ \ldots\ R$. As mentioned, such system cannot be exactly solved because of the noise and estimation inaccuracies, in fact a pair (ξ_e, η_e) that satisfy all the equations likely does not exist. We should thus resort to a LSE-like procedure: It requires first to define the target functions:

$$U_e(\xi_e,\eta_e) \stackrel{\text{def}}{=} \frac{1}{R-1}\sum_{r=2}^{R}\big|(1-\rho_{er}^2)(\xi_e^2+\eta_e^2) - \rho_{er}^2[(r-1)^2Y^2 - 2(r-1)Y\eta_e]\big|^\alpha\ , \tag{6}$$

for $e = 1,\ 2,\ \ldots\ E$. In the pure LSE case the coefficient $\alpha = 2$, while choosing a different value allows adding robustness to the estimation. The minimal value of U_e may be found by a numerical procedure.

4. EXPERIMENTAL RESULTS

In the first experiment we considered a problem counting $R = 8$ receivers/sensors and $E = 4$ emitters/sources. The Figure 3 shows the result of localization when the source separation is performed through the JADE algorithm; as a particular result pertaining to this experiment, Figure 4 shows the shape of the cost function (6) for one of the emitters, which shows that the function is rather sharp in cor-

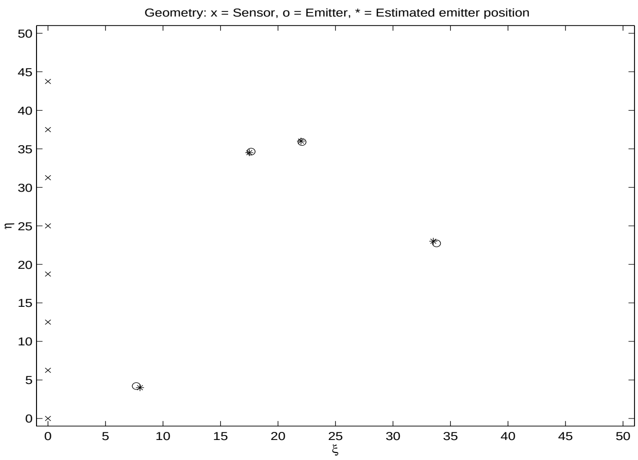

Fig. 3. Geometry of the problem and estimated source positions.

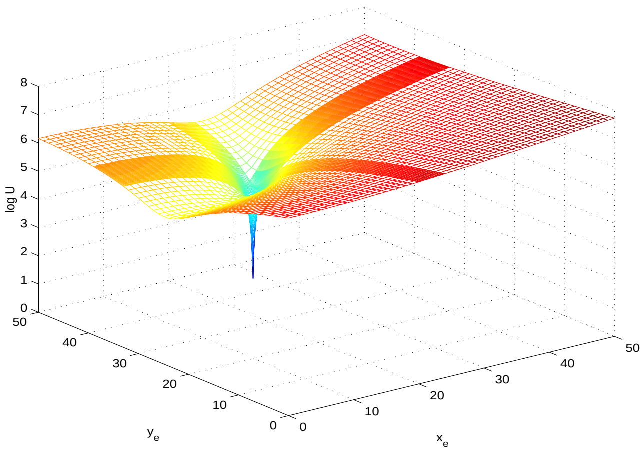

Fig. 4. Exemplary shape of the cost function (6) for an emitter.

respondence to the minimum, thus the estimation is quite reliable.

It is important to remark that by the ICA algorithm it is impossible to give any ordering to the recovered signals, thus it is important to extract some further information from the separated source signals. To this aim, an important set of parameters that can be estimated from the emitted signals is the set of carrier frequencies. Figure 5 shows the spectra of the network output signals, from which it is very easy to locate the centers of each spectrum that corresponds to the carrier.

As a final comment, another important parameter which needs to be extracted from the mixed signals is the power of the emitted field from each antenna. Having the mixture and the set of recovered source signals (whose power gets often

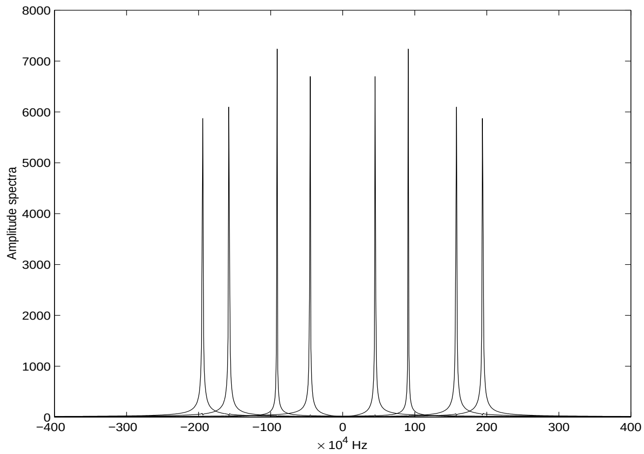

Fig. 5. Spectra of the 4 network output signals, used in order to recover the carriers frequencies, which help labeling the emitters.

automatically normalized to one) it is possible to estimate such powers; once again, however, standard Fourier analysis is practicable only for narrow-band signals, while in general a more general correlation procedure is to be employed: The correlation among the mixtures and each of their components give the mixing coefficient, that can be multiplied by the proper distance to give the amplitude of the emitted field. (If necessary, such power may be later subject to an inverse-weighting by the antenna's spectral function in order to retrieve the power truly supplied to each antenna.)

The core of the estimation procedure is the ICA algorithm: As mentioned, in this paper we wish to compare the properties of JADE and CFP algorithms run on the described data. As objective measures of the algorithms' performances we took the following two indices: 1) the source location estimation error (SLE), defined as:

$$SLE = \frac{1}{E}\sqrt{\sum_{n=1}^{E}[(\xi_n^E - \xi_n^R)^2 + (\eta_n^E - \eta_n^R)^2]}\,; \qquad (7)$$

note that in our experiments $(\xi, \eta) \in [0, 50] \times [0, 50]$; 2) the number of floating point operations (flops) required by each algorithm to run. In order to make the resulting numbers as independent as possible from statistical fluctuations, we present the results averaged over 20 independent trials on 15,000 observed samples. Note that the JADE algorithm requires to set a statistical threshold for stopping the joint diagonalization, which was fixed at $(1/\sqrt{N})/10000$, where N denotes the number of input samples; also, the FPC requires setting the number of iterations of the fixed point search algorithm, which was set to 5, in these experiments.

ALGORITHM	Ave. SLE	Ave. Flops ($\times 10^7$)
JADE	4.65	6.85
CFP	4.76	6.12

Table 1. SLE and flops for the JADE and CFP algorithms, averaged over 20 independent trials. (Geometry: $E = 4$, $R = 8$.)

ALGORITHM	Ave. SLE	Ave. Flops ($\times 10^7$)
JADE	3.09	2.62
CFP	2.17	2.84

Table 2. SLE and flops for the JADE and CFP algorithms, averaged over 20 independent trials. (Geometry: $E = 2$, $R = 8$.)

The obtained results are summarized in the Table 1 for the case $E = 4$ and $R = 8$, while Table 2 refers to the case $E = 2$ and $R = 8$. The two algorithms do not exhibit noticeable differences in the performances and in the complexity, while their performance betters when the number of emitters decreases.

To conclude these experiments, we used the results given by ICA algorithms in order to estimate the powers of the emitted fields from each antenna. The Table 3 shows the results of such estimation using the JADE algorithm to separate out the contributions of each emitter, while Table 4 refers to the CFP algorithm; both pertain to the case $E = 4$, $R = 8$, $\alpha = 2$. Once again, the results are rather accurate and the two algorithms do not differ in performance; as mentioned, this is an important issue in order to plan the emission reduction scheme for the stations.

5. CONCLUSIONS

The aim of this paper was to propose the application of complex-valued ICA to blind separation of propagated signals in order to blindly retrieve the location (and possibly the emitted power) of the emission station with electromagnetic pollution monitoring purposes. Two algorithms, namely the JADE and CFP have been applied to this kind of data and their features have been numerically investigated.

EMIS. POW. (W)	E_1	E_2	E_3	E_4
True	19.34	18.97	30.46	68.22
Estimated	19.25	19.05	30.23	68.38

Table 3. True and estimated powers for the four emitters (Algorithm: JADE).

EMIS. POW. (W)	E_1	E_2	E_3	E_4
True	87.57	73.73	13.65	1.15
Estimated	86.99	73.78	13.50	1.17

Table 4. True and estimated powers for the four emitters (Algorithm: CFP).

6. ACKNOWLEDGMENT

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