A Feasibility Study for Electromagnetic Pollution Monitoring by Electromagnetic-Source Localization via Neural 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), as a part of a feasibility study for electromagnetic pollution monitoring via neural network techniques. Four ICA algorithms known from the literature, allowing to process complex-valued signals, are used to estimate the propagation parameters of electromagnetic fields emitted by radio-base transmission systems. By properly interpreting the results given by the ICA algorithms it is possible to develop a blind source localization procedure. The experiments are performed on synthetic signals generated according to real-world emission features, and are used to obtain a preliminary evaluation of the expected behavior of the localization system in a real-world context.

1. Introduction

The continual growth of the telecommunication industry, with special reference 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 wide territorial areas have caused the spatial density of radiated fields to constantly increase, so that many countries have promoted and approved central or local government laws, or adopted national or international standards, as regulation for the control and the limitation of the electromagnetic fields generated by radio-telecommunication stations [1,2,3,4,5].

These regulations usually include the control of the generated electromagnetic field levels in two different steps:

1) *Authorization* – In order to obtain the authorization for building-up a new radio-telecommunication station, or for the substantial modification of an existing one, the electromagnetic field produced in the environment must be predicted during station's design; moreover the electromagnetic field in the environment must be measured after the station has been realized;

2) *Environmental control* – The electromagnetic fields are periodically measured, in order to control if the limits are exceeded. In this case, according to the different regulations and procedures, all the interested emitting stations, and their exact locations, must be determined. In addition, the fraction of the electromagnetic field produced for each emitting station must be evaluated, in order to compute the power reduction factor to be applied to each transmitting station, or to apply other equivalent methods of reduction to conformity.

A problem similar to the one evidenced in point (2) can be found in case of interference between two or more transmitting stations or channels. In this case, the individuation of the interfering antennas and/or transmitting stations is often a difficult task especially when the interference is due to a local emitter: The size of the antennas, in fact, could be small and their location could be difficult to recognize by aerial view or by other similar searching methods.

The existence of the mentioned law limits and measurement difficulties imposes the development of suitable procedures, allowing to measure the intensity of the fields in a given location, in order to verify if the law-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 analysis 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 aim at recovering the source signals from their mixtures [6,7,8,9,10,11,12,13,14,15], 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. 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 [16,17,18].

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 [11,19].

In particular, in this paper we present a possible approach to the exploitation of the behavior of the electric field versus time, measured quasi-simultaneously in different locations, via a suitable neural network technique, to reconstruct each separate contribute. When the emitted electric field, and the related base frequencies, or channels, have been separated for each emitter, the unknown locations of each antenna, or emitting systems, are determined with a numerical technique.

The theory here presented has been applied with success to a practical problem dealing with amplitude-modulated radio-transmissions, and the obtained results are meant as the first step of a feasibility study.

2. Overview of Independent Component Analysis

The Independent Component Analysis (ICA) [6,7,8,9,10,11,12,13,14,15,29] is a well-established statistical signal processing technique that aims at decomposing a set of multivariate signals into a base of signals *as statistically independent as possible*, with the minimal loss of information content. The main two recognized purposes of ICA are:

- *Data representation and visualization*: High-dimensionality signals are difficult to handle and to visualize, but often contain significant redundancies, which make their actual information-structure dimensionality considerably lower than their representation dimensionality. These concurrent facts suggest the need of signal processing algorithms capable of finding a suitable lower-dimensionality representation of the signals at hand by reducing the statistical dependencies among them. In this context, the independent component analysis technique has proven to provide a suitable solution through the concept of *independent latent variables*: The ICA may discover a linear projection of the data into a low-dimensional basis of statistically independent signals, that carry on no mutual information, thus providing a parsimonious maximally-informative representation of the original data. The basis data-streams are termed latent variables, which do not necessarily possess a recognizable physical meaning;

- *Linear blind source separation*: In this case the aim is to recover a number of statistically independent signals from their unknown linear mixtures, under simple consistency conditions. Namely, a linear mixture of independent source signals is supposed to be observed, and on the basis of these only available information, the original source signals are recovered from their mixtures, provided some minimal consistency conditions are met; such minimal set of requirements ensures the existence and uniqueness of the solution to the blind separation problem (but for ordering and scaling), the minimal loss of information about the sources and, as a by-product, the identification of the mixing model features.

Much theoretical research work has been carried out by several researchers over recent years in order both to produce ever refined algorithms for performing independent component analysis, and to publish consistent results about the basic theory of ICA (concerning the signals models and the solvability of the analysis problem related to these models) and about the algorithmic-level theory (concerning the theoretical study of the relevant properties of the different classes of algorithms, such as convergence, reliability, computational burden, equivariancy, and implementation questions).

The number of available contributions in the independent component analysis field is motivated by the wide variety of different observed-signals models considered in the applied areas. The main distinctions are between:

- *Linear or non-linear mixing*: In the simplest (though much representative) case, the mixing model is linear. Otherwise, some kinds of non-linear structures have been considered, such as the post-linear mixing model, in order to take into account e.g. the non-linear distortion introduced by the measurement systems;

- *Real-valued or complex-valued models*: In some applied fields, such as e.g. in telecommunications, it is useful to treat the involved signals as complex-valued data-streams, thus dedicated algorithms have been developed for complex-valued models handling;

- *Instantaneous or convolutional mixture*: When the relationship describing the formation of the observed signals/data from the source/latent signals does not take into account the temporal structure of the latter, i.e. the linear mixing operator is constant over time, the model is termed instantaneous. Otherwise, a convolutional model can be considered, which described the observed signals as the results of multiple linear filtering applied to the source/latent streams;

- *Square, over- and under-determined mixtures*: The number of available measures may be equal to the number of source signals in blind separation, in which case the mixture is termed square. From a practical point of view this hypothesis is not always realistic: The cases where the number of sources is larger or smaller than the number of observations are properly represented by the over- and under-determined models.

- *Noiseless or noisy mixtures*: The signals model may or may not take into account the possible presence of additive disturbance affecting the measured signals.

- *Stationary or non-stationary model*: The hypothesis of having stationary source/latent signals is not always realistic; real-world random signals may exhibit time-fluctuations of their statistical features, and this phenomenon may affect the performance of the independent component analysis if not properly taken into account. In opposition to stationary models, non-stationary ones try to capture the non-stationarity of the sources and to make the related ICA algorithm take advantage of this knowledge.

Concurrently, the scientific community has manifested an ever increasing interest in the ICA technique and, generally speaking, in the blind signal processing research field, because it provides a powerful tool for signal processing, comparable in importance to the older principal component analysis. Known applications range from speech recognition to fault detection, from telecommunications to medical imaging, from financial data market analysis to biological data pre-processing, and from industrial plant identification to non-destructive evaluation [14,16,17,22,23,24,25,26,27,28,30].

In the present paper, in order to solve the mentioned reduction-to-conformity problem, we consider complex-valued sources and a linear, instantaneous, quasi-stationary, noisy model for the observed signals.

In order to carry out source separation, we consider four independent component analysis techniques, namely:

- *The JADE algorithm* [9]: It performs source separation via a Joint Approximate Diagonalization of Eigen-matrices. This is a Jacobi algorithm because the joint diagonalizer is found by a Jacobi technique, where plane rotations are applied to cumulant matrices.
- *The complex-fixed-point (CFP) algorithm* [20]: This is fixed-point type algorithm for the separation of linearly mixed, complex-valued signals in the ICA framework. It is based on a deflationary separation of independent components. The algorithm is robust against outliers and computationally simple, and the estimator given by the algorithm is locally consistent.
- *The Extended Hebbian learning (EHA) algorithm* [19]: It is a non-linear extension to Sanger's generalized Hebbian learning algorithm for complex-valued data neural processing, which allows for separating mixed independent circular source signals. The proposed generalization relies on an interesting interpretation of non-classical Hebbian learning proposed by Sudjianto and Hassoun for real-valued neural units.
- *The y-cAPEX class of learning rules* [11,21]: It arises as a generalization of Hebbian learning theory for complex-weighted linear feed-forward network endowed with lateral inhibitory connections, and to show how it can be applied to blind separation from complex-valued mixtures. It obtains from an optimization principle for Kung-Diamantaras' principal component network which leads to a generalized APEX-like learning theory.

The practical application of ICA algorithms requires to perform a pre-processing step: The available data should be subjected to *pre-whitening*, which consists in removing first-order and second-order statistics from the data. Some ICA algorithms explicitly require this operation to be performed, while other known algorithms do not need pre-whitening; however, it has been experimentally observed that whitening facilitates independent components extraction, because it facilitates algorithm convergence [24]; also, the analysis of the covariance matrix of data, and in particular of its eigenstructure, may reveal some interesting property about the data's information-structure dimension.

An ICA algorithm applied to the whitened data allows extracting the desired number of independent components. In the present context the model of the data is linear, complex-valued, and instantaneous. As mentioned, the JADE and CFP algorithms are of batch-type: They come with no internal parameters to adjust and iterate the tuning of separation structure until no changes of the internal state occur. The EHA and ψ-cAPEX algorithms are instead of on-line type: They update the separation structure once for every available input sample and make the separating network learn through one single sweep of the data; they require the network learning step-size to be carefully tuned on a case-by-case basis.

3. Formal models

In this section we present the formal models of signals and electromagnetic propagation employed in the present paper in order to represent the reduction-to-conformity problem, a well as the fundamentals of source localization technique.

3.1 Model of electromagnetic source superposition

In the electromagnetic source separation model, we suppose a mixture of statistically independent source signals is observed:

$$\boldsymbol{u}(t) = \boldsymbol{M} \cdot \boldsymbol{s}(t) \tag{1}$$

where $\boldsymbol{M}$ is an unknown constant complex-valued full-rank $m \times n$ mixing matrix and $\boldsymbol{s}(t)$ is the vector-stream containing the n source signals to be separated. The only hypotheses made on the unknown sources are:

1) Each $s_i(t)$ is an independent identically distributed (IID) stationary random process;
2) The $s_i(t)$'s are statistically independent at any time;
3) At most one among the source signals may have Gaussian distribution.
4) The number m of observations exceeds the number n of sources.

For separating out the independent sources from their linear mixture, a neural network with m inputs and n outputs can be used; this network is described by the relationship:

$$\boldsymbol{o}(t) = \boldsymbol{W} \cdot \boldsymbol{u}(t) \qquad (2)$$

where $\boldsymbol{u}(t)$ is the neural network input vector and $\boldsymbol{W}$ denotes the network connection-matrix. As the mixing model is linear, a linear separating structure is effective, and the network's output $\boldsymbol{o}(t)$ is taken as an estimate of the true source stream $\boldsymbol{s}(t)$. Under the above conditions, the sources may be recovered up to arbitrary scaling and permutation [10].

As a by-product, an estimate of the mixing matrix $\boldsymbol{M}$ can be obtained, which describes the physics of wave-propagation in the source localization and assessment problem. In fact, under the cylindrical wave propagation hypothesis, it can be readily seen that the entries M_{rc} have the structure:

$$M_{\mathrm{rc}} = f(d_{\mathrm{rc}})\exp(\mathrm{j}\gamma d_{\mathrm{rc}}) \qquad (3)$$

where the function $f(.)$ describes the emitted energy loss and the phasor accounts for the emitted field phase rotation, due to wave propagation, and d_{rc} denotes the distance between the r-th emitter and the c-th receiver. Consequently, each row of the estimated mixing matrix, normalized to e.g. its first entry, equals the electrical field ratio between the field emitted by an antenna, as received by a sensor, and the field emitted by the same antenna as received by the first sensor.

3.2 Model of emitted signals

The emitting stations perform radio-transmissions at frequencies in the range of frequencies dedicated to the Amplitude Modulation (A.M.) transmissions (500 kHz - 2MHz) and with the typical emission power of these antennas (5-200 kW).

The time-dynamics of the emitted signals follows the Amplitude-Modulation model, i.e. the source signals have the expression:

$$s_{\mathrm{i}}(t) = (1+m_{\mathrm{a}} \cdot m_{\mathrm{i}}(t))\cos(w_0 \cdot t + j\,) \qquad (4)$$

with $m_{\mathrm{i}}(t)$ being the modulating signal, m_{a} being the amplitude-modulation depth, and w_0 and j being the carrier frequency and phase, respectively.

3.3 Model of electromagnetic field propagation and triangularization

The electric field value emitted by an electromagnetic source S in a point $\mathrm{P_i}$ in the free space is a function of the distance between the source and the point, and it can be written in the following form:

$$E_i = h(x_i, y_i, x, y) \tag{5}$$

where E_i is the electric field value in the point P_i, (x_i, y_i) are the Cartesian coordinates of the point P_i, and (x, y) are the Cartesian coordinates of the source position. In our problem we have a set of electric field ratio for a specific source carried out from the separation algorithm described in the previous paragraph. In order to identify the antenna position we can define the following functions from (5):

$$g_{rc}(x, y) = \frac{E_r}{E_c} \cdot h(x_c, y_c, x, y) - h(x_r, y_r, x, y) \tag{6}$$

$$G(x, y) = \sqrt{\sum_{r=1}^{m} \sum_{c=1}^{m} g_{rc}^2(x, y)} \tag{7}$$

where m is again the number of the points considered, E_r/E_c is the electric field strength ratio for two generic points P_r and P_c and h is the function of the electric field amplitude versus antenna coordinates for the typical radio-transmission antenna considered. This formulation gives estimation results that prove invariant to arbitrary scaling factors. In particular, the coordinate-pairs (x,y) that minimize function G coincide to sources positions, thus numerical minimization of this criterion is required. The procedure utilized in the present paper, based on the above mathematical formulation of electromagnetic field propagation, which allows finding the emitting sources by minimization of the misfit function G is hereafter referred to as triangularization algorithm.

The relationship between the energy-loss function f(.) and the antenna characteristic function (5) is:

$$f(d_{rc}) = h(x_r, y_r, x_c, y_c) \tag{8}$$

The analytical expression for the electromagnetic-energy propagation model comes from real-world measurements of typical radio-telecommunication stations, and reads:

$$f(d) = A_1 e^{-d/d_1} + A_2 e^{-d/d_2} + A_3 e^{-d/d_3} + \frac{A_4}{d}\left(1 - e^{-d/d_4}\right)$$

where constants A_1, A_2, A_3, A_4 and d_1, d_2, d_3 and d_4 have been computed by numerical fitting, as shown in Figure 1, with two *measured* curves. The obtained curve f(.) is consistent with the theoretical knowledge about electromagnetic field propagation laws [4].

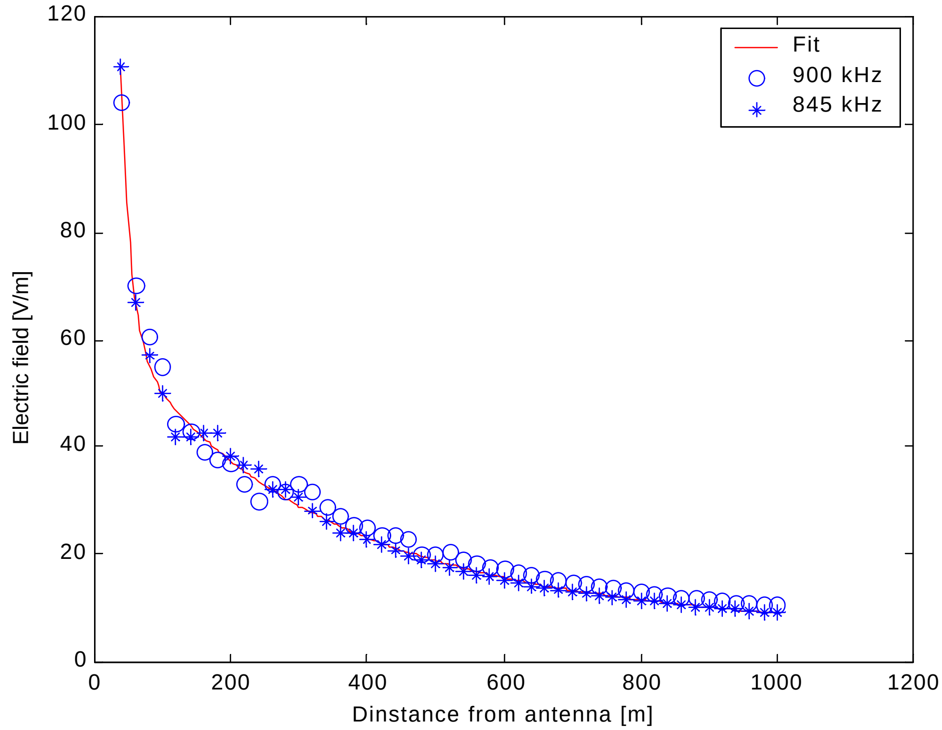

Fig. 1: Zoom of comparison of fitted electrical field attenuation curve and two measured curves.

As mentioned, when several electromagnetic field sources are present in the region of the space under attention, for each antenna it is possible to estimate its position by the relative set of electric fields ratio provided by the separation algorithm, using the inverse procedure presented above.

The electric field ratios pertaining to each emitter-sensor pair may be estimated by the help of blind separation in the following way: The separation algorithm knows the measurements vector-stream $\boldsymbol{u}(t)$ and estimates the source vector-stream $\boldsymbol{s}(t)$; now it is easy to get an estimate of the propagation operator $\boldsymbol{M}$; by definition, the propagation operator entries are complex numbers, whose moduli are proportional to the value of function $f(.)$ computed on the distance between the related emitter and sensor. Formally, by taking into account the mentioned possible indeterminacy factors introduced by the separation algorithm [10], we can write the estimated propagator as:

$$\left|\hat{\boldsymbol{M}}\right| = \begin{bmatrix} k_1 f(d_{11}) & k_1 f(d_{12}) & k_1 f(d_{13}) & \cdots \\ k_2 f(d_{21}) & k_1 f(d_{22}) & k_1 f(d_{23}) & \cdots \\ \vdots & & & \end{bmatrix}$$

where the unknown constants k_1, k_2, ..., take into account the possible constant-amplitude distortions introduced by independent component analysis. On the basis of these considerations, it is easily recognized that by normalizing the first entry of each row by the respective first entry, we get red of unknown scaling factors and obtain the mentioned set of electrical field ratios, which are the entries of the numerical matrix:

$$\begin{bmatrix} 1 & \dfrac{f(d_{12})}{f(d_{11})} & \dfrac{f(d_{13})}{f(d_{11})} & \cdots \\ 1 & \dfrac{f(d_{22})}{f(d_{21})} & \dfrac{f(d_{23})}{f(d_{21})} & \cdots \\ \vdots & & & \\ & & & \end{bmatrix}$$

4. Experimental Results

With the mentioned working hypotheses, a set of three emitting stations has been randomly generated and simulated, and an environmental electromagnetic noise - perceived as a fourth source - has been generated as well, with a signal-to-noise ratio (SNR) of about 1.

The considered source signals have the structure (4), where: The carriers have frequencies in the range 900kHz - 1MHz; the carrier phases are random; the amplitude-modulation depth is $m_a = 0.8$; the $m_\mathrm{i}(t)$ are speech signals sampled at a frequency of about 11kHz; the area interested of source search is a square of 200km of side.

Each of the four considered separation algorithm has been tested on four possible configuration of the measurement points, namely: Linear-array, 'L'-shaped-array, uniform grid, and random-shaped array, in order to investigate on the effect of measurement points disposition on source localization performances. The reason for such test is that the performance of the localization algorithm likely depends on the mean distance between the sensors and the emitters, because the sensitivity of the algorithm is not uniform with the distances: As a matter of fact, the ability of the triangularization algorithm to resolve among two sensors is related to the slope of the antenna function f(.) with respect to distance, or to the *sensitivity* summarized by the curves of Figure 2.

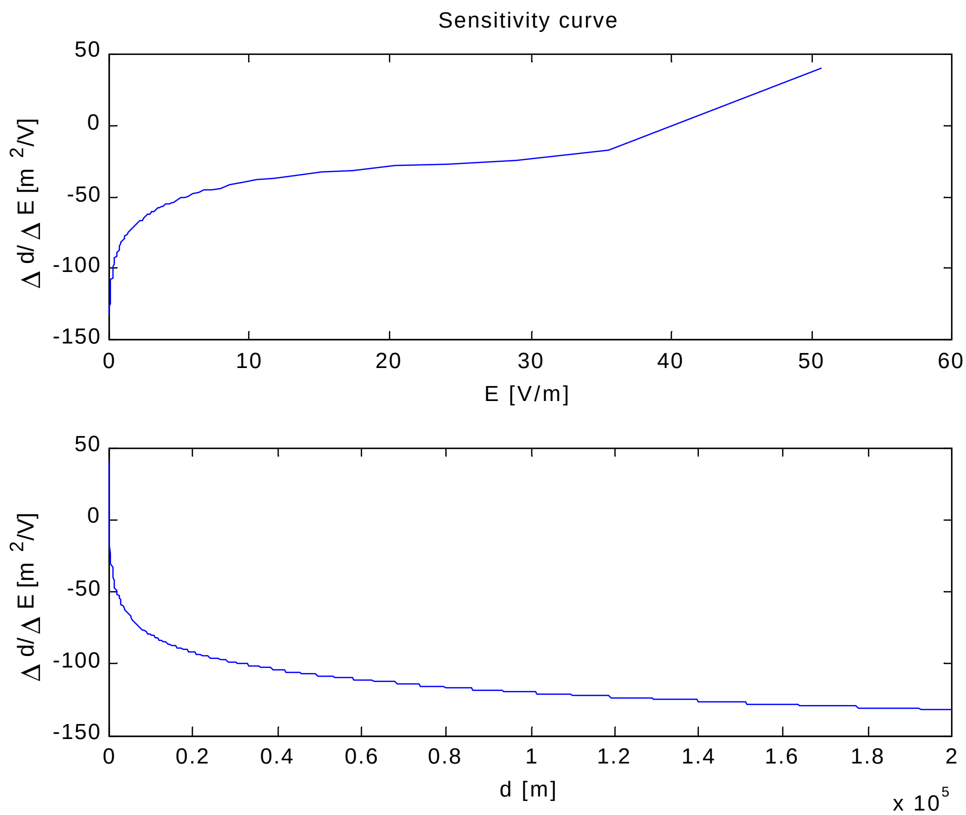

Fig. 2: Sensitivity in dB of the localization algorithm versus field amplitude (top) and distance (bottom).

The sensitivity is defines as the ratio $\Delta d/\Delta E$, and represents the amount of distance change Δd require to produce a change ΔE of measured field $E = f(d)$. Low values of the measured field, corresponding to high values of the sensor-emitter distance, give rise to low sensitivity values corresponding to worse estimation of emitter location.

In conclusion, it is expected that measures configuration corresponding to a smaller mean-distance with the emitters would give rise to better estimates.

The objective performances of the source separation-localization procedure are assessed in terms of the following three figures-of-merit:

- *Sum of Localization Errors (SLE)*: Over a completely known set-up both the disposition of the measurement points and of the emitters are known, and this allows to numerically evaluate the precision that the emission stations are localized with. The square-root of the sum of square-differences among the true coordinates of the emitters and the estimates provided by the localization algorithm is retained as measure of procedure performance;

- *Total floating-point operations required*: A MATLAB-code implementation of the mentioned algorithm has been employed to test the performances of the suggested source-localization procedure. The four considered algorithms exhibit different complexity-levels, which are measured in terms of the total floating-point operations (flops) required by the codes to run on a common platform (256MB of memory, 500MHz machine):

- *Total CPU computation time*: Another interesting parameter from a practical point of view is the estimate of computation time required by a dedicated machine to run the mentioned code. This is measured by the total CPU computation time required by the implemented code when run on a common platform.

While total flops and computation time are absolute performance measures, the SLE figure-of-merit needs a term of comparison in order to be objectively evaluated. To this aim, it is worth noting that the error in the emitters localization is due to two concurrent causes: 1) The imprecision of the used blind source separation algorithm, resulting in an imprecision in the estimation of the propagation operator; 2) The imprecision of the triangularization procedure based on the value of propagation operator. About the above point 2), it is worth remarking that the cost function (6), used to find the sources within the search-area, is evaluated numerically by partitioning the whole search-area in small squares through a uniformly-spaced grid and by searching the sources over grid's nodes. The imprecision of the triangularization comes from the density of the grid. In particular, under the hypothesis that the estimation-error contribution due to the separation algorithm is null, the only contribution remaining to explain the estimation error is due to triangularization. The maximum error owing to triangularization can be easily evaluated by considering the worst estimation case, that arises when the true source lays exactly in the center of a grid-square and the algorithms tries to assign it to one of the corner of the square: By denoting as l the side of the grid-squares, the error is proportional to the semi-diagonal of the square, that is:

$$SLE^{tri} = l \big/ \sqrt{2}$$

In our case we used a uniform grid of 100×100 squares, thus l = 200,000/100 m = 2km; this leads to about SLE^{tri} = 1,400 m, which we assume thus as our term of comparison for the value of SLE provided by the different separation-localization algorithms.

For every considered measurement set-up, a single-trial experiment is shown and discussed in order to clarify the set-up conditions; also, the average performance of the separation-localization procedures are illustrated by averaging the above-mentioned performance indexes over a set of 30 independent trials. A constant of the algorithms and of the different simulations is that they operate on 15,000 available simulated measurement samples and the on-line-type algorithm run with learning-stepsizes that do not change during the different experiments; the constancy of these conditions allow us to objectively evaluate the behavior of the different techniques in the different operative situations.

4.1 Experiments with a linear-array disposition of measures

The first set of experiments concerns the test of the four algorithms on a linear array of measures. A single-trial experiment is shown in the Figure 3, which clarifies the disposition of sensors and shows a typical result. The average results of experiments are reported in Table 1.

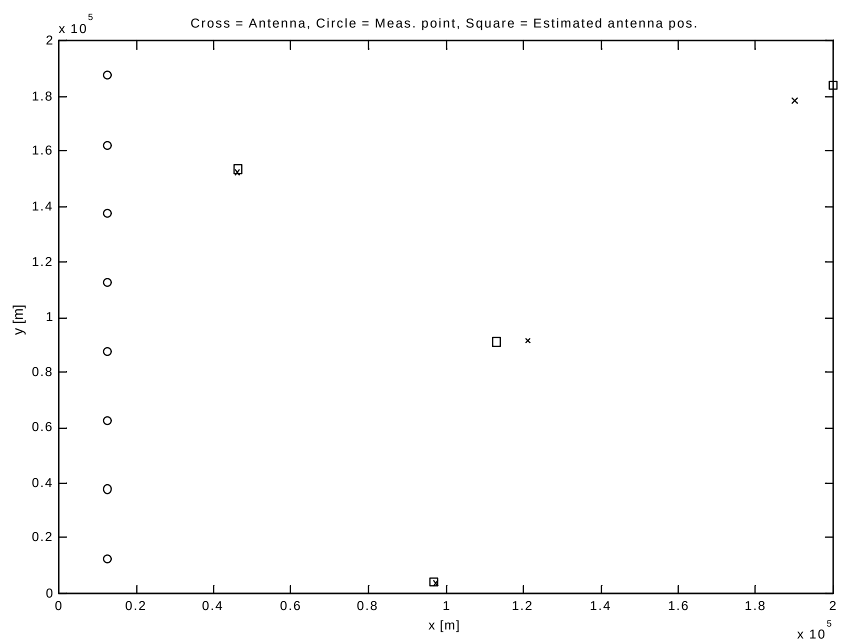

Fig. 3: A single-trial experiment with JADE algorithm on linear array of measurements.

Algorithm	SLE (km)	Flops	Time (s)
JADE	6.9	66350557	104

Algorithm	SLE (km)	Flops	Time (s)
CFP	11	59040547	161
EGHA	23	41554162	107
ψ-APEX	27	86884880	113

Tab. 1: Average SLE, flops and computation time for source localization with a linear array of measurements.

The single-trial experiments as well as the results of the averaged analysis show the linear array of measures is not really well suited for source localization, because the average distance among the sources and the sensor is high, making the algorithm work on the least sensitive part of antenna curve.

4.2 Experiments with a 'L'-shaped-array disposition of measures

The second set of experiments concerns the test of the four algorithms on a 'L'-shaped array of measures, which should guarantee better performances of the algorithm with respect to linear array of sensors. A single-trial experiment is shown in the Figure 4, which clarifies the disposition of sensors and shows a typical result. The average results of experiments are reported in Table 2.

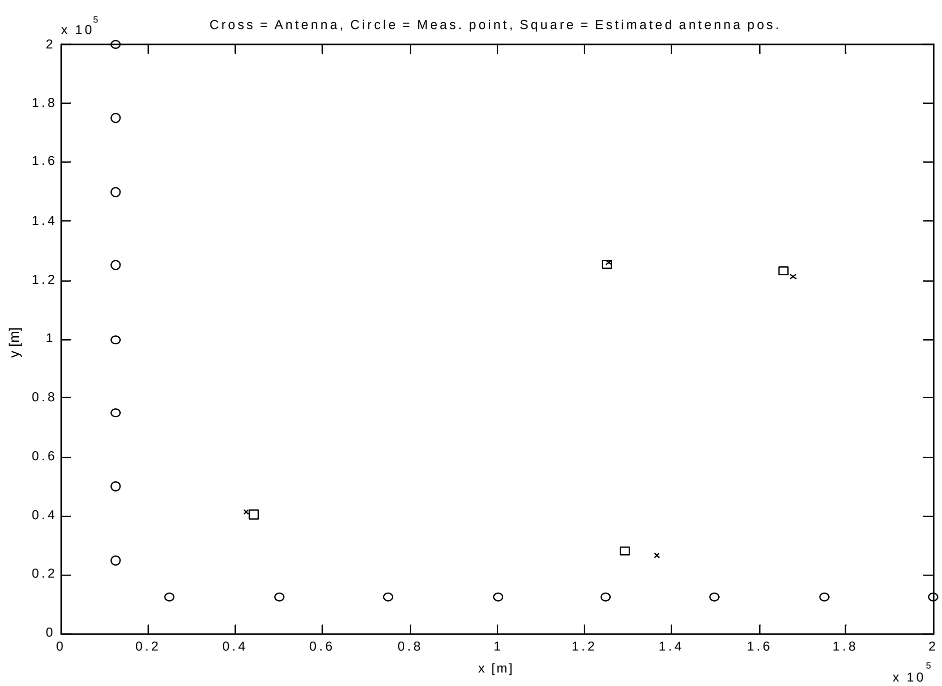

Fig. 4: A single-trial experiment with JADE algorithm on 'L'-shaped array of measurements.

Algorithm	SLE (km)	Flops	Time (s)
JADE	8.3	66990579	99
CFP	13	60880664	180
EGHA	29	42239309	103
ψ-APEX	27	87573690	114

Tab. 2: Average SLE, flops and computation time for source localization with a 'L'-shaped array of measurements.

The single-trial experiments as well as the results of the averaged analysis show the 'L'-shaped array of measures is more suited than the linear one, because the average distance among the sources and the sensor is higher, making the algorithm work on the least sensitive part of antenna curve.

However, the result of this conceptual experiment opens room for discussion, in that it clearly emerges that one of the sources, located in about (130, 25) [kilometers], which finds quite near one of the branches of the 'L'-shaped array of sensors, has been located with an unexpectedly large estimation error. A possible explanation of this result comes from a close examination of the Figure 4: The well-estimated sources lie near a diagonal line across the squared area-of-interest, while the badly-estimated source lies off such diagonal line. This suggests that such particular disposition of sensors suffers of some orientation effect, possibly due to severe phase interference of the electromagnetic waves, which *makes the whole sensor array blind outside the main array diagonal*. This clearly makes the discussed sensor configuration unsuitable for general-purpose source localization and assessment.

4.3 Experiments with a grid-disposition of measures

The third set of experiments concerns the test of the four algorithms on a grid disposition of measures, which is the natural extension of a 'L'-shaped grid of measurement points. A single-trial experiment is shown in the Figure 5, which clarifies the disposition of sensors and shows a typical result. The average results of experiments are reported in Table 3.

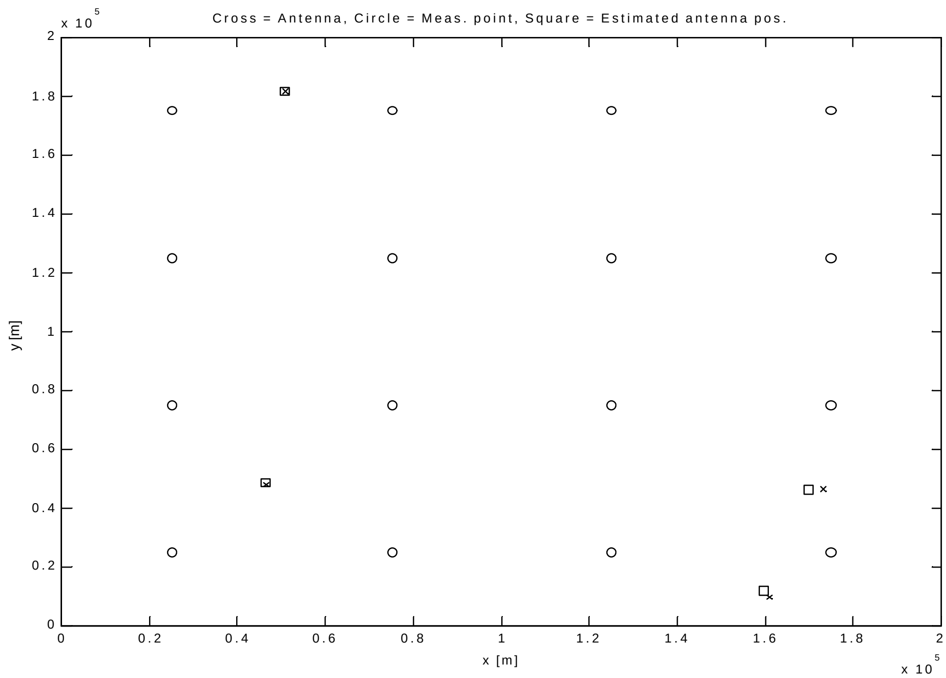

Fig. 5: A single-trial experiment with JADE algorithm on regular-grid array of measurements.

Algorithm	SLE (km)	Flops	Time (s)
JADE	2.3	104242752	205
CFP	3.6	96931695	260
EGHA	6.6	79445611	210
ψ-APEX	6.6	24798795	216

Tab. 3: Average SLE, flops and computation time for source localization with regular-grid array of measurements.

The results show a very good agreement between the true antennas disposition and the estimated antenna positions, confirming that a regular grid of measurements is among the best possible choices.

4.4 Experiments with a random disposition of measures

The last set of experiments concerns the test of the four algorithms on a completely random disposition of measures. A single-trial experiment is shown in the Figure 6, which clarifies the disposition of sensors and shows a typical result. The average results of experiments are reported in Table 4.

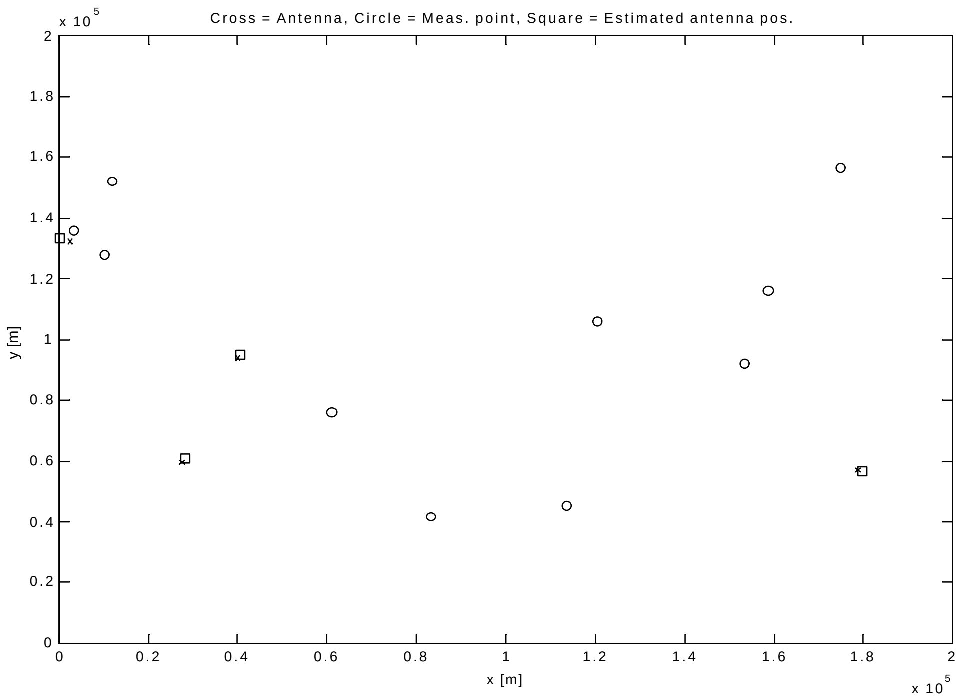

Fig. 6: A single-trial experiment with JADE algorithm on random disposition of measurements.

Algorithm	SLE (km)	Flops	Time (s)
JADE	4.5	74345397	144
CFP	5.7	670375202	212
EGHA	12	49550347	150
ψ-APEX	13	94901959	157

Tab. 4: Average SLE, flops and computation time for source localization with a random disposition of measurements.

The results show an acceptable agreement between the true antennas disposition and the estimated antenna positions, if compared to the comparison term triangularization error term, telling that a random grid of measurements is another acceptable choice.

5. Conclusion, Discussion and Further Work

In this paper we have proposed an hybrid technique that allows in a first step the separation of the electromagnetic signals in the time-domain, via a blind source separation neural algorithm, and in a second step the individuation of the positions of each antenna, via a numerical inversion algorithm.

The theory described in the paper has been applied to a practical problem dealing with amplitude-modulated radio-transmissions and tested with real-world antenna features. We tested four blind separation algorithms and four possible sensor configurations, in order to numerically investigate on the behavior of the proposed source localization algorithms. A comparative analysis among the sixteen possible cases clearly shows that the JADE algorithm appears as the most suited algorithm, in the present case, and the regular-grid array of measures appears as the best configuration among those considered here.

The present paper is essentially of experimental nature and aimed at proving the feasibility of the envisaged approach, through conceptual experiments conducted in a completely controlled setting, and at individuating the best suited algorithm for processing the considered data, among the many algorithms available in the scientific literature about blind source separation by the neural independent component analysis and by statistical signal processing techniques.

From a theoretical point of view, it would be of sure interest to carry out a deep analytical investigation among the common as well as the distinctive features of the different considered algorithms. It is in fact worth considering here that they have been derived starting from quite different perspectives: The JADE algorithm is based on a joint diagonalization of high-order statistical tensors and requires the estimation of these tensors and the exploitation of a sophisticated algorithm for jointly diagonalize them by Jacobi rotators; the CFP bases on the minimization of a non-linear function of network parameters, which barely recalls the well-known kurtosis extremization principle, and exploits a fast fixed-point algorithm for achieving minimization; the EHA relies on a constrained gradient descent minimum-search algorithm applied to the minimization of a non-linear function of network parameters, where the constraints are enforced through a Lagrange-multipliers technique; the ψ-cAPEX algorithm is based on a neural topology exhibiting lateral inhibitory connections endowed with a own learning criterion/procedure. It is also well-known from both neural networks and signal processing literature that several different separating structures and adaptation theories have been developed on the basis of different starting principles, all of which lead to effective blind separation procedures, showing that the research activity in this field benefited from a large scattering in several directions. However, the huge variety of principles and algorithms related to blind signal separation makes the analytical comparison among the available algorithms hard to carry out and, to the best of our knowledge, no systematic investigation about the interrelationships among them has been presented. Some recent efforts in this direction may be however found in the recently published books [31,32].

The conclusion of the presented analysis is that the obtained preliminary results presented here seem to be promising, and are encouraging as a feasibility study for electromagnetic pollution monitoring by unsupervised neural networks. In particular, the result of conceptual experiments suggest that, in general, a single estimation-iteration with the available measures would not be enough in order for the reduction-to-conformity procedure to give rise to reliable result, because the average SLE in the best found case is somewhat greater than the minimum error expected from the area-of-interest partition; a possible way to overcome this difficulty would be to operate with a second set of field-measures, to be taken in correspondence of the estimated source position, and to proceed with a new estimation phase aimed at refining the old estimates.

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References

[1] ICNIRP: *Guidelines for limiting exposure to time-varying electric, magnetic, and electromagnetic fields (Up to 300 GHz)*, Health Physics, Vol. 74, No. 4, pp. 494 - 522, Apr. 1998

[2] IEEE Std. C.95.1-1999, *IEEE Standard for safety levels with respect to human exposure to radio-frequency electromagnetic fields*, 3kHz - 300 GHz, New York, 1999

[3] IEEE Std. C.95.3-1991, *IEEE Recommended practice for the measurements of potentially hazardous electromagnetic fields - RF and microwave*, New York 1991

[4] D. Slater, *Near Field Antenna Measurements*, Artech House, 1991

[5] ITU-R Rec.S.M.326-7, *Determination and measurements of the power of amplitude-modulated radio transmitters*, 1998

[6] A.J. Bell and T.J. Sejnowski, *An information maximisation approach to blind separation and blind deconvolution*, Neural Computation, Vol. 7, No. 6, pp. 1129 - 1159, 1995

[7] S. Fiori, *A Theory for Learning by Weight Flow on Stiefel-Grassman Manifold*, Neural Computation, Vol. 13, No. 7, pp. 1625 - 1647, July 2001

[8] S. Fiori, *Blind signal processing by the adaptive activation function network*, Neural Networks, Vol. 13, No. 6, pp. 597 - 611, Aug. 2000

[9] J.-F. Cardoso and A. Souloumiac, *Blind beamforming for non Gaussian signals*, IEE Proceedings-F, Vol. 140, No. 6, pp. 362 - 370, Dec. 1993

[10] P. Comon, *Independent Component Analysis, A new concept ?*, Signal Processing, Vol. 36, pp. 287 - 314, 1994

[11] S. Fiori, *Blind Separation of Circularly Distributed Source Signals by the Neural Extended APEX Algorithm*, Neurocomputing, Vol. 34, No. 1-4, pp. 239 - 252, Aug. 2000

[12] X. Giannakopoulos, J. Karhunen, and E. Oja, *An Experimental Comparison of Neural Algorithms for Independent Component Analysis and Blind Separation*, International Journal of Neural Systems, Vol. 9, No. 2, pp. 99 – 114, 1999

[13] M. Girolami and C. Fyfe, *Extraction of independent signal sources using a deflationary exploratory projection pursuit network with lateral inhibition*, IEE Proceedings - Vision, Image and Signal Processing, Vol. 14, No. 5, pp. 299 – 306, 1997

[14] A. Hyvärinen and E. Oja, *Independent component analysis: algorithms and applications*, Neural Networks, 13 , 411 – 430, 2000

[15] H.H. Yang and S.-i. Amari, *Adaptive Online Learning Algorithms for Blind Separation: Maximum Entropy and Minimum Mutual Information*, Neural Computation, Vol. 9, pp. 1457 – 1482, 1997

[16] A. Flexer and H. Bauer, *Monitoring human information processing via intelligent data analysis of EEG recordings*, Intelligent Data Analysis, Vol. 4, pp. 113 - 128,

2000

[17] R. Vigario and E. Oja, *Independence: A new criterion for the analysis of the electromagnetic fields in the global brain ?*, Neural Networks, Vol. 13, No. 8/9, 2000

[18] H.J. Wieringa, *MEG, EEG and the integration with Magnetic Resonance Images*, Ph.D. Thesis, University of Twente, Enschede, The Netherlands, Oct. 1993

[19] S. Fiori, *On Blind Separation of Complex-Valued Sources by Extended Hebbian Learning*, IEEE Signal Processing Letters, Vol. 8, No. 8, pp. 217 - 220, 2001

[20] E. Bingham and A. Hyvärinen, *A fast fixed-point algorithm for independent component analysis of complex valued signals*, International Journal of Neural Systems, Vol. 10, No. 1, pp. 1 - 8, Feb. 2000

[21] S. Fiori and F. Piazza, *A General Class of ψ-APEX PCA Neural Algorithms*, IEEE Transactions on Circuits and Systems - Part I, Vol. 47, No. 9, pp. 1394 - 1398, 2000

[22] A. Cichocki and J. Cao, *A self-adaptive neural network for on-line blind separation of convolved sources*, Topics on Non-destructive Evaluation Series, Eds. B.B. Djordjevic and H.D. Reis, Vol. 3, The American Society for Non-destructive Evaluation Testing, Inc., pp. 207 - 212, 1998

[23] C. H. Chen and X. Zhan, *On the roles of independent component analysis in remote sensing*, Proc. of Progress in Electromagnetics Research Symposium (PIERS'2000), Cambridge (MA, USA), 2000

[24] X. Giannakopoulos, J. Karhunen, and E. Oja, *An Experimental Comparison of Neural Algorithms for Independent Component Analysis and Blind Separation*, International Journal of Neural Systems, Vol. 9, No. 2, pp. 99 - 114, 1999

[25] K.H. Knuth, *Bayesian source separation and localization*, In A. Mohammad-Djafari (Ed.), SPIE'98 Proceedings: Bayesian Inference for Inverse Problems, San Diego, pp. 147 - 158, 1998

[26] S. Fiori and P. Burrascano, *ECT-Data Fusion by the Independent Component Analysis for Non-Destructuve Evaluation of Metallic Slabs*, Third International Conference on Independent Component Analysis and Signal Separation, pp. 323 - 327, San Diego, California, December 9-13, 2001

[27] A. Ypma, *Creating virtual sensors for machine monitoring with independent component analysis*, (in Dutch), Journal of the Acoustical Society of the Netherlands, No. 145, pp. 1 - 12, March 1999

[28] R.-w. Liu, *Blind Signal Processing: An Introduction*, Proc. of International Symposium on Circuits and Systems (IEEE-ISCAS), Vol. 2, pp. 81 - 84, 1996

[29] S. Fiori, *A Theory for Learning Based on Rigid Bodies Dynamics*, IEEE Trans. on Neural Networks, Vol. 13, No. 3, pp, 521 - 531, May 2002

[30] Y. Deville, *Towards industrial applications of blind source separation and independent component analysis*, Proc. of Independent Component Analysis Conference (ICA'99), pp. 19 - 24, 1999

[31] T.-W. Lee, *Independent Component Analysis - Theory and Practice*, Kluwer Academic Publisher, 1998

[32] A. Hyvärinen, J. Karhunen, and E. Oja, *Independent Component Analysis*, John Wiley & Sons, 2001