Numerical Modeling for the Localization and the Assessment of Electromagnetic Field Sources

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Abstract— **In this work we present a possible approach to electromagnetic source localization using a hybrid blind separation - minimum search inversion algorithm. The total electrical field versus time, emitted by the working antennas located at different and unknown geographical positions, is used, via a suitable blind signal processing technique based on neural networks, to reconstruct each separate contribute. When the emitted electric signals have been separated for each emitting antenna, the unknown locations of the antennas are determined with a minimum-search numerical technique.**

Indexing terms– **Electromagnetic emission control; Blind source separation; Neural networks; Non-linear propagation model inversion.**

I. Introduction

THE expansion of the telecommunication industry, with special reference to cellular phone and radio-TV broadcasting systems, has raised the alerting of the public opinion and of the governments about the electromagnetic pollution phenomena.

As a matter of 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. As a reaction, many countries have promoted and approved central or local laws, or adopted national or international standards, as regulation for the measurement and the limitation of the electromagnetic fields [1], [2], [3].

These regulations include the control of the generated electromagnetic field levels and concern the procedures to obtain the authorization for building-up a new emission station, or to substantially modify an existing station. The regulations also require the electromagnetic fields to be periodically measured, in order to check if the limits are exceeded.

When law-limits violations are noticed, the interested emitting stations, their exact locations and emission powers should be determined and an emission reduction plan should be made effective. The existence of the mentioned law limits and measurement difficulties imposes the development of suitable measurement procedures. In fact, in case of violation the global information about the total measured field does not suffice to react in the proper way: It is necessary to individuate the set of emission-stations insisting on the volume under observation along with their single emission parameters. The first step consists in the electromagnetic sources localization. The scenario that this operation 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.

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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 neural independent component analysis may be envisaged in order to blindly recover the source signals and, as an useful by-product, to locate the sources themselves.

The aim of blind source separation (BSS) is to separate out unobservable or latent source signals when mixed signals only are observed, with little or no knowledge about the source statistics nor their temporal characteristics. In particular, under the hypothesis that the source signals to be separated out are statistically independent, the independent component analysis (ICA) theory [4], [5], [7] may be employed.

Over recent years, blind source separation by the independent component analysis has received much attention owing to its potential applications, as in speech recognition systems, telecommunications, fault detection, medical imaging, and other important research fields (for a recent review see [6], [8], [9], [10], [12]).

The classical techniques aimed only at recovering the source signals from their mixtures, while only very recently the attention has been turned to the mixing operators, which may reveal important information about the geometry of the sources and the signal propagation models, that appear buried into the observed data.

The aim of this paper is to present an application of 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 and the power of the emitted electromagnetic field. The last operation should be performed through a non-linear model inversion, which allows identifying and locating the sources on the basis of predicted deflated measures.

II. Theory

In this section we present the signal and propagation model, the basic ICA theory and the non-linear model inversion theory, aimed at electromagnetic source separation, localization and assessment.

A. Signal and propagation model

Within the present work we consider the emitting stations perform radio-transmissions at frequencies in the range dedicated to the Amplitude Modulation (AM) transmissions. The time-dynamics of the emitted signals have thus the expression:

$$s_i(t) = (1 + m_a \cdot m_i(t)) \cos(\omega_i t + \phi_i) \ , \ i = 1, ..., E \ , \quad (1)$$

where $m_i(t)$ are the modulating signals, m_a denotes the amplitude-modulation depth, and ω_i and ϕ_i are the carrier frequencies and phases, respectively; E denotes the total number of emitters insisting on the volume of space under consideration. For blind separation purposes, the only hypotheses made on the sources $s_i(t)$ 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 possess Gaussian statistics.

In the complex-valued notation, the measured signals through R virtual electromagnetic receivers are supposed to obey the following linear composition model:

$$\mathbf{x}(t) = \mathbf{P}^H \mathbf{s}(t) + \mathbf{n}(t) \ , \quad (2)$$

where $\mathbf{x}(t)$ is the observed R-dimensional random vector-signal, $\mathbf{P}$ is a constant complex-valued $R \times E$ 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 exceeds or equates the number of true sources, thus we consider the technical hypothesis $R \geq E$. It is important to stress out that, in our experimental setting, both the propagation operator $\mathbf{P}$ and the source signals $s_i(t)$ are unknown, because the only measures $x_i(t)$ are physically accessible.

For separating out the linearly mixed independent sources from their measures, we use a neural network, whose training theory is the subject of the subsection II-B. 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. As this operation is always possible, from now on we always suppose the network has E inputs and E outputs.

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

$$\mathbf{y}(t) = \mathbf{W}^H(t)\mathbf{x}(t) \ , \quad (3)$$

where $\mathbf{y}$ 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 (3) is taken as a noisy estimate of the true source stream $\mathbf{s}(t)$. As a useful by-product, once the source signals have been estimated, an estimate of the propagator becomes easily available, too, which allows performing the source localization procedure.

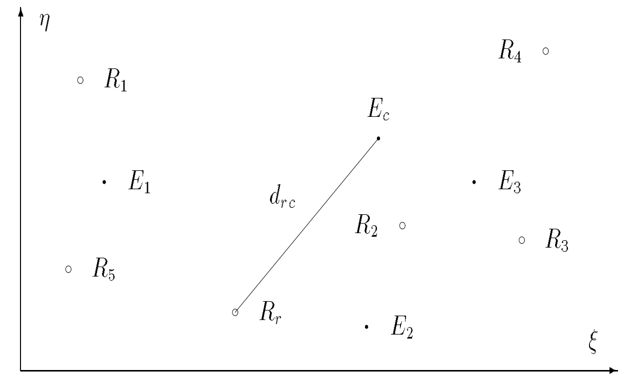

Fig. 1. Exemplary description of the problem-geometry and of the used notation (dots = sources; open circles = measurement-points).

About propagator $\mathbf{P}$, in our setting we 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 the pair (ξ_i^R, η_i^R), $i = 1, ..., R$. A typical emitters/sensors configuration is depicted in the Figure 1.

For source localization purposes, it is necessary to envisage a relationship that links the propagator-matrix entries to the geographical positions of the emitters and of the measuring sensors. To this aim, the (r, c)th entry of the propagation matrix $\mathbf{P}$ is described by the phasor:

$$P_{rc} = f(d_{rc}) \exp[-j\gamma d_{rc}] \ , \quad (4)$$

$$d_{rc} = \sqrt{(\xi_r^E - \xi_c^R)^2 + (\eta_r^E - \eta_c^R)^2} \ , \quad (5)$$

where γ denotes the constant of propagation and the function $f(\cdot)$ describes the electromagnetic energy-loss during propagation, so that each phasor accounts for the loss of the wave-energy and of phase-rotation during propagation. A typical energy-loss function was obtained by analytically fitting two measured curves, pertaining to AM emission antennas, and is shown in the Figure 2. The fitting model has the expression:

$$f(d) = a_1 e^{-d/d_1} + a_2 e^{-d/d_2} + a_3 e^{-d/d_3} + \frac{a_4}{d} \left(1 - e^{-d/d_4}\right) \ ,$$

with the parameters obtained by the least-square fitting of the measured antennas behavior.

For blind separation purposes, we add the further hypothesis, on the propagator, that (d) $\mathbf{P}$ is a full-column rank matrix.

B. Independent Component Analysis

A network separating configuration should of course satisfy $\mathbf{W}^H \mathbf{P}^H \sim \mathbf{I}$, so that $\mathbf{y}(t) \sim \mathbf{s}(t)$, that is equivalent to say that $\mathbf{W}$ should be as close as possible to the pseudo-inverse of $\mathbf{P}$. This closed-form solution is however infeasible because, as already mentioned, $\mathbf{P}$ is unknown.

Neural independent component analysis aims at separating out statistically independent signals from their linear

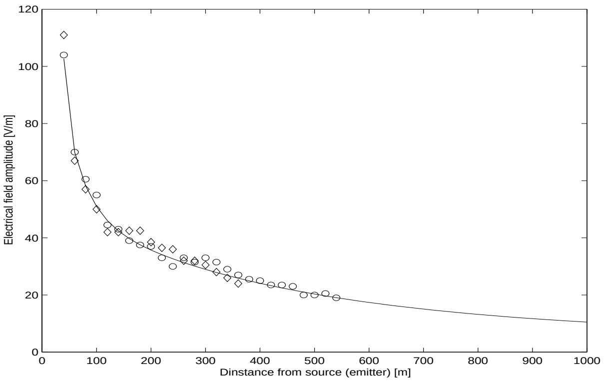

Fig. 2. A typical energy-loss function obtained by analytically fitting two measured curves.

mixtures. The mixture model is as in (2) and the neural separating structure is as in (3). Basic ICA theory ensures that, under the hypothesis (a)-(d) above, the ICA problem admits solutions: The source signals may be recovered up to arbitrary reordering, scaling and phase rotation [7].

The basic principle that the independent component analysis theory is based on, is that after application of the mixing model (2), the observed signals $x_i(t)$ are no longer statistically independent, because mixing model (2) constructs mixtures of independent signals which clearly are not independent. In order to achieve separation, the neural-network weight-matrix may be learnt so that the network's outputs (3) become as independent as possible, that is, they meet the complete factorization property, which for the network's outputs writes:

$$p_{\mathbf{y}}(\mathbf{y}) = p_{y_1}(y_1)p_{y_2}(y_2)\cdots p_{y_E}(y_E) \ , \qquad (6)$$

where $p_{\mathbf{y}}(\mathbf{y})$ denotes the joint probability density function of the sources, and:

$$p_{y_i}(y_i) \stackrel{\text{def}}{=} \int_{\mathcal{R}^{E-1}} p_{\mathbf{y}}(\mathbf{y}) dy_1 \cdots dy_{i-1} dy_{i+1} \cdots dy_E \ .$$

A way to achieve separation is thus to define a measure of the mismatch between the two sides of the equation (6), and a learning algorithm to iteratively adjust the weight-matrix in order to minimize this disagreement. From a methodological point of view, this expression of the ICA principle looks really suggestive, because a computable measure of discrepancy between the joint probability density function of network's outputs and the product of their marginal density functions plays the role of a (non-computable) measure of distance between $\mathbf{W}$ and the unknown pseudo-inverse of $\mathbf{P}$.

Several possible mismatch measures have been reported in the scientific literature during the last years. Among others, here we recall a very interesting and fruitful one which relies on mutual information (MI). Using usual information-theory notation, the MI of network outputs defines as:

$$\mathcal{I}_{\mathbf{y}} \stackrel{\text{def}}{=} \int_{\mathcal{R}^E} p_{\mathbf{y}}(\mathbf{y}) \log \frac{p_{\mathbf{y}}(\mathbf{y})}{p_{y_1}(y_1)p_{y_2}(y_2)\cdots p_{y_E}(y_E)} d\mathbf{y} \ , \qquad (7)$$

which is a special case of a Kullback-Leibler informational divergence, and enjoys the property $\mathcal{I} \geq 0$.

Straightforward computations lead to the expanded expression:

$$\mathcal{I}_{\mathbf{y}}(\mathbf{W}) = -\mathcal{H}_{\mathbf{x}} - |\det(\mathbf{W})|^{-1} - \sum_{i=1}^{E} \langle \log p_{y_i}(y_i) \rangle_{\mathbf{x}} \ , \qquad (8)$$

where $\mathcal{H}_{\mathbf{x}}$ denotes the Shannon differential entropy of the multivariate random process $\mathbf{x}$, which does not depend upon matrix $\mathbf{W}$, and $\langle \cdot \rangle_{\mathbf{x}}$ denotes statistical expectation.

This may be retained the starting point for the practical design of learning algorithms. An intensive research work has been carried out in the neural-network and signal-processing fields about the MMI principle, and several simplifications and practical considerations have led to a number of running algorithms for performing blind source separation by the independent component analysis theory. The explanation of these details falls outside the scope of the present paper: We mention that, after a careful analysis of some algorithms available in the scientific literature, we chose to employ the JADE algorithm [5] which guarantees excellent source/propagator estimation at the cost of reasonable computational burden.

C. Non-linear propagation model inversion

The BSS algorithm provides an estimate of the signals emitted by the polluting antenna, from which carrier frequencies can be extracted in order to 'label' the sources, and an estimate of the propagator, namely $\hat{\mathbf{P}}$.

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 only one entry per row different from zero [7] (this formally accounts for arbitrary re-ordering and complex scaling).

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

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

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 still unknown.

The dependence on the unknown k_i may now be easily got rid of by e.g. normalizing each row about its first element, which makes available the ratios $|P_{rc}|/|P_{r1}|$. If $R \geq 3$, we can then approximately localize 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 over-complete set of non-linear equations in

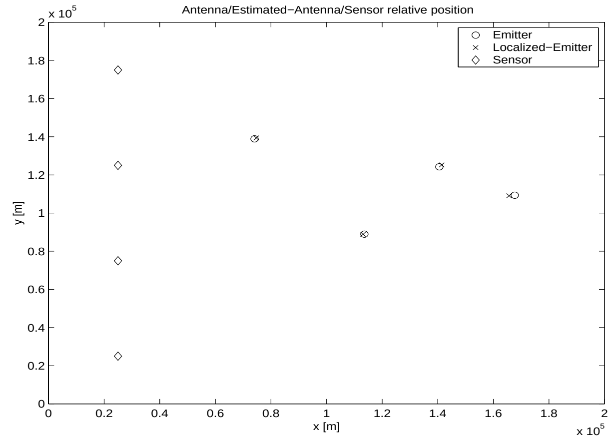

Fig. 3. Emitters, sensors, estimated-emitters in experiment 1.

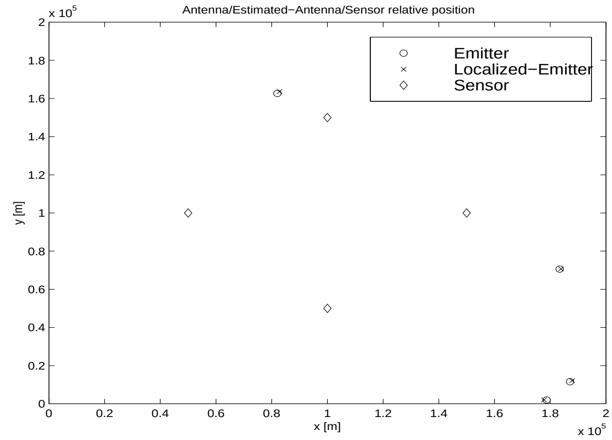

Fig. 4. Emitters, sensors, estimated-emitters in experiment 2.

the two unknowns. The solutions may thus be determined by a (robust) non-linear least-error (NLE) procedure: For each emitter, we can construct the non-linear cost function:

$$C_e(\xi_e^E, \eta_e^E) = \frac{1}{R} \sum_{c=1}^{R} \left| \frac{f(d_{ec})}{f(d_{e1})} - \frac{|P_{ec}|}{|P_{e1}|} \right|^{\alpha} , \tag{9}$$

to be minimized with respect to emitters coordinate pairs (ξ_e^E, η_e^E) e.g. by a numerical minimum-search algorithm. The constant α above is a robustness parameter: $\alpha = 2$ leads to standard non-linear least-squares cost function.

III. Results, Discussion, Conclusion

The considered set-up is as follows: The carriers have frequencies in the range 900kHz - 1MHz; the carrier phases are random; the amplitude-modulation depth is $m_a = 0.8$; the $m_i(t)$ are speech signals sampled at a frequency of 22kHz; the geographical area individuated for source-search is a square of 200km of side.

The figures-of-merit employed for procedure evaluation are: (1) Sum of Localization Errors (SLE): Over a completely controlled test set-up both the coordinates of the sensors and of the emitters are known; 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 localization performance; (2) Total floating-point operations required by a MATLAB-code implementation of the mentioned algorithm to run on a common platform (256MB of memory, 500MHz machine); (3) Total CPU computation-time required by the algorithm to run on the platform.

Through several exoeriments we validated the localization algorithm and chose as best robustness parameter value $\alpha = 1.6$.

The first experimental result concerns the emitter/linear-array-sensor geometry displayed in the Figure 3. The same Figure also shows the estimate of the emitter positions as computed by the proposed algorithm: The estimate in this case is quite good (the SLE amounts at 0.66km for a total computation burden of 48,613,009 flops in about 53 seconds).

The second experimental result concerns the square-array-sensor geometry displayed in the Figure 4. The Figure also shows the estimate of the emitter positions: Even in this case the estimate is quite good (the SLE amounts at 0.48km; the computational burden is similar to the one pertaining to the first experiment because again NR=NE=4).

In both experiments the results were really encouraging and suggest pursuing the described research work. Efforts will be made in order to take into account more realistic propagation models and to apply the proposed technique to real-world (measured) signal processing.

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