Identification of brain activity by stochastic algorithms

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***Abstract*—The identification of electrical activity inside the brain requires to find the position and amplitude of electrical sources related to neural energizing. This task is approached by means of an optimization algorithm trying to find the minimum error between the electric potential created by a current dipole source and the one obtained by an electroencephalographic experiment. The identification problem is carried on a discretized head model obtained by a segmentation of MRI data. Brain activity is experimentally studied by fMRI technique to identify the active region of electrical activity. The optimization algorithm used is Artificial Immune System and its performances are first studied on a model problem. Results obtained are encouraging both in terms of accuracy and of convergence speed.**

***Index Terms*—Bioelectric fields, inverse EEG, source localization.**

I. Introduction

The localization problem of brain sources from scalp potential recordings is a key problem in computational bio- electromagnetism, and its solution is an active research field [1]. Primary sources are generally modeled as ideal point current dipoles. In the up-to-date literature the source location inverse problem from the knowledge of scalp potentials is commonly solved by Nelder-Mead simplex method [2]. The functional to be minimized is a suitable norm of the reconstruction error. The identification problem is known to be ill-posed [3], thus the simplex method requires multi-start and it can fail when the nodes of the simplex fall inside a single element. In this paper the identification problem is solved by means of AIS a stochastic algorithm whose main characteristic is the ability of searching optimal solution in multimodal objective function landscapes.

II. AIS algorithm

Artificial Immune systems are a class of algorithms inspired by the working of biological immune systems. Their common idea is related to the exploration of the objective function landscape by several different *antibodies* which are points in configuration space. As in nature the strength point of the immune system is based on diversity of antibodies, so that they can fight with different pathogen issues at the same time, also in optimization different searching points can find their way toward the optimum. As a complete description of the scheme can be found in [4], here only its main characteristics are described. The algorithm is structured in two nested loops, as outlined in Fig. 1. In the inner loop two operators are applied to the population: cloning and mutation and clonal selection. The individuals of the previous iteration, called memory cells, are reproduced in copies of the original. Then, each clone is locally mutated by a random perturbation, in order to find a high-affinity (high-fitness) cell. The best mutated clone for each cell replaces the original memory cell. In the outer cycle the affinity and suppression operators are applied to the population. The Euclidean distance between memory cells is measured; all but the highest fitness cells whose distances are less than a threshold are suppressed. The suppressed cells are then replaced with new randomly generated cells. In order to maintain the diversity of solutions and to obtain a good exploration of the space of the parameters, at each iteration a minimum number of new cells is guaranteed. Both loops end if the average fitness of the memory cells does not improve between two iterations or if the number of iterations reaches the maximum value.

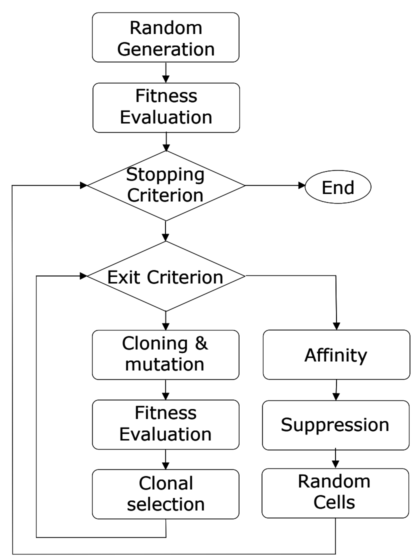


Fig. 1. Flowchart of the *opt-aiNet* algorithm.

TABLE I
GEOMETRY AND TISSUE PROPERTIES ($f_{\text{ref}} = 20$ Hz)

tissue	**outer radius** cm	**conductivity** S/m
scalp	9.2	0.43478
skull	8.74	0.00625
CSF	8.28	1.538
gray matter	7.82	0.3334
white matter	7.37	0.1428

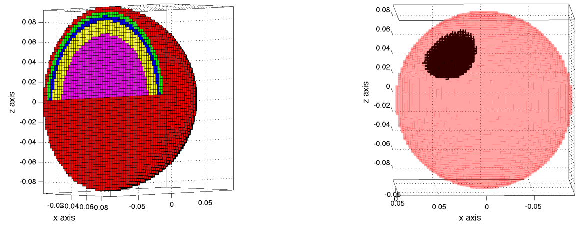
III. MODEL PROBLEM

The testing phase of the algorithm is performed on a model problem whose characteristics (number of unknowns, amplitude of active region etc.) can be easily changed for working purposes. The problem geometry is a modified five-layer spherical model Fig. 2(a): the geometrical and material parameters are reported in Table I. This discretization is characterized by 61565 hexahedra and 67368 nodes. The Active region is defined as the intersection of an ellipsoid of given centre and axes and the set of grey and white matter, as it can be seen in Fig. 2(b). The Lead field matrix is computed by means of a Cell Method approach as it has been described in [5], [6].

The direct problem is then defined by setting arbitrarily the position, orientation and amplitude of a current dipole inside the active region and computing the electric potential on a set of seventeen electrodes on sphere surface. On this set of data an objective function is defined as the quadratic norm of the error of the potentials created by a current dipole and those previously computed. The degrees of freedom of the objective function are the (x, y, z) coordinates of a dipole and its three components of current orientation (i_x, i_y, i_z). These two sets of variables are not treated in the same way: current dipole components are set, once position is defined, by means of a normal equation approach, which implies the solution of a linear system of the number of electrodes dimensions. The position of the dipole is managed by the AIS algorithm as previously described. Due to the regular mesh discretization, the step of the mutation of position is taken as a small multiple of the mesh amplitude size.

The objective function landscape is not regular and its exploration has been attempted by using a Pattern Search algorithm starting it from every point of the active region. In the present case, out of 1067 nodes belonging to the active region, only 12 Pattern Search runs were able to find the global optimum and the position of the starting points were not contiguous so that it was not possible to define a compact area of attraction of the minimum. Preliminary results obtained on the model problem in a case with a number of degrees of freedom comparable with the actual head discretization, allow to state that the procedure is working correctly and that it is able to find the global optimum in a number of trials which is always lower than 16% of the whole number of configurations. Procedure will be tuned up on the model problem and then it will be tested on the head. Results on the head will be presented at the conference. In the full-length paper the case study will be solved also in terms of a bi-objective optimization problem [7], the objective functions being:

- discrepancy between reference potential and computed potential on the scalp, to be minimized with respect to the dipole position, and
- number of activated edges in the cell grid discretizing the active region, to be minimized too in order to cut spurious solutions off. The comparison with results from AIS will follow. In particular, the role played by major operators in each algorithm (like mutation in AIS and cross-over in multi-objective procedure) will be discussed.



(a) (b)

Fig. 2. (a) Discretization of the model problem, and (b) active region used in the optimization.

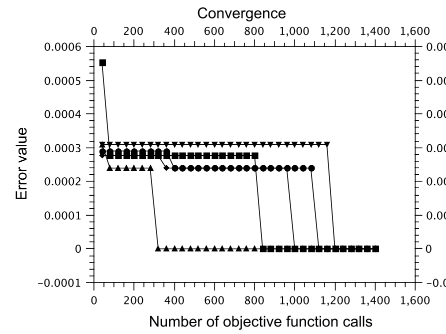


Fig. 3. Convergence plot in five different optimization runs.

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