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1. INTRODUCTION

In the last years, significant efforts have been made to develop unsupervised systems able to detect landmines or unexploded ordnances for both military and civilian purposes. Several solutions have been proposed based on different methodologies to face this problem in a fast and effective way [1]. In such a framework, learning-by-examples (LBE) techniques [2][3] have demonstrated to be promising solutions able to enable detection procedures efficient in terms of both resolution and required time/computational resources.
This paper is aimed at describing the detection problem as a three-dimensional classification process and analyzing its extension from theory to real experiments through a careful numerical analysis. Thanks to an integrated strategy based on a Support Vector Machine (SVM) classifier and a multi-resolution approach, a multi-resolution detection is obtained by means of an iterative zooming that considers only the regions characterized by an high probability to be occupied by the buried object. The arising time and computational saving allows the definition of an high-resolution map despite the complexity of the three-dimensional scenario at hand.

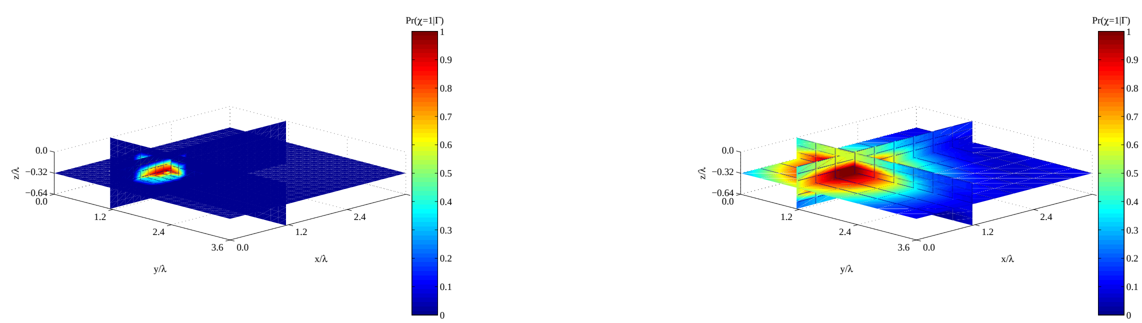
2. MATHEMATICAL FORMULATION

Let us consider a three-dimensional investigation domain, characterized by a relative dielectric permittivity ε_d and a conductivity σ_d. A set of P buried objects are located at unknown positions (x_p, y_p, z_p); $p = 1,..., P$. Each object is modeled as a finite-length cylinder of radius r_o and height h_o of electrical properties ε_o and σ_o. Above the investigation domain surface, a set of N sensors measures the electromagnetic field $\mathbf{E}_t(x, y, z)$ scattered at different positions (x_n, y_n, z_n); $n = 1,..., N$ when a dipolar-like source at (x_s, y_s, z_s) illuminates the scenario under analysis. By assuming the knowledge of the soil, it is then possible to determine the so-called scattered field $\mathbf{E}_s(x, y, z) = \dfrac{\mathbf{E}_t(x, y, z) - \mathbf{E}_i(x, y, z)}{\mathbf{E}_i(x, y, z)}$ defined as the normalized difference between the measured electromagnetic field with (i.e., $\mathbf{E}_t$) and without (i.e., $\mathbf{E}_i$) the unknown buried objects. The problem at hand is that of localizing the unknown objects starting from the available field values, $\Psi = \{\mathbf{E}_s(x_n, y_n, z_n); n = 1,..., N\}$. The problem is then recast as a classification one aimed at defining a three-dimensional probability map of the presence of the buried objects inside the investigation domain. In order to achieve a suitable spatial resolution, a multi-step strategy based on a synthetic zooming is used.
More specifically, at the initialization step ($s = 0$), the investigation domain is partitioned into M three-dimensional cubic cells centered at the locations $(x_m^{(0)}, y_m^{(0)}, z_m^{(0)})$; $m = 1,..., M$ of a uniform lattice. The m-th cuboid is "occupied" (i.e. $\chi_m^{(0)} = +1$), if a buried object lies in the m-th sub-domain, otherwise it is labeled as "empty" (i.e. $\chi_m^{(0)} = -1$). For each cell, it is possible to define the *a posteriori* probability $p_m^{(0)} = \Pr\{\chi_m^{(0)} = +1 \mid \Psi\}$, that it belongs to the "occupied"

class [3] starting from the knowledge of the array Ψ .Therefore, the probability vector $\mathbf{P}^{(0)} = \left\{p_m^{(0)}; m = 1,..., M\right\}$ has to be estimated to compute a complete probability map of the whole investigation domain. Such a classification problem, where only two classes are admissible, can be profitably solved by means of a SVM-based [4] approach, assuming the knowledge of a set of K input-output relations $\left[\left(x_k, y_k, z_k\right), \chi_k\right]_k; k = 1,..., K$ called *training set*. Once the classification has been performed, it is possible to identify on the probability map a set of *Regions of Interest* (ROIs), where the probability values are greater than a fixed user-defined threshold p_{th}. The synthetic zooming is then successively performed by partitioning the ROIs in M three-dimensional cells of coordinates $\left(x_m^{(1)}, y_m^{(1)}, z_m^{(1)}\right); m = 1,..., M$. Such a zooming procedure is iterated until a suitable spatial resolution is achieved or until a stationary condition on the dimension of the ROIs between two consecutive steps holds true. Accordingly, the final probability map is fully determined by $\mathbf{P}^{(s_{opt})} = \left\{p_m^{(s_{opt})}; m = 1,..., M\right\}$.

3. NUMERICAL RESULTS

In order to assess the reliability and effectiveness of the iterative SVM approach, but also its feasibility in a real environment, several numerical simulations have been carried out. More specifically, realistic scenarios have been carefully modeled and some representative results are shown in the following. As an example, let us consider the test case of a buried object ($\varepsilon_o = 2.5$, $\sigma_o = 0$) is located at $\left(x_o = 1.17\lambda, y_o = 1.17\lambda, z_o = -0.32\lambda\right)$ in an investigation domain ($\varepsilon_d = 4.0$, $\sigma_d = 0.004$) of dimension $3.6\lambda \times 3.6\lambda \times 0.64\lambda$. A set of $N = 100$ sensors has been uniformly distributed on a plane 0.1λ above the surface to collect the electromagnetic field samples, while a source located at $\left(x_s = 1.84\lambda, y_s = 1.84\lambda, z_s = 0.1\lambda\right)$ illuminated the scenario. Concerning the SVM classifier, a training set of $K = 300$ samples has been generated by means of a FEM electromagnetic simulator. Finally, the scattering data have been blurred by adding a Gaussian random noise ($SNR = 30dB$). The estimated probabilities along the three orthogonal planes passing through the center of the buried object are shown in Fig. 1(*a*). For comparison purposes, the result obtained with the single-resolution approach is shown [Fig. 1(*b*)] as well. As it can be observed, the zooming approach allows one to obtain a more accurate localization of the object.



(*a*) (*b*)

Figure 1 – Estimated probabilities for (*a*) the zooming technique and (*b*) the standard approach.

5. REFERENCES

[1] *IEEE Trans. Geosci. Remote Sens.*, Special Issue on: “New Advances in Subsurface Sensing: Systems, modeling and Signal Processing,” vol. 32, Jun. 2001.

[2] I. T. Rekanos, “Inverse scattering of dielectric cylinders by using radial basis function neural networks,” *Radio Sci.*, vol. 36, no. 5, pp. 841-849, 2001.

[3] A. Massa, A. Boni, and M. Donelli, "A classification approach based on SVM for electromagnetic subsurface sensing," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, pp. 2084-2093, Sep. 2005.
[4] V. Vapnick, *Statistical Learning Theory*, Wiley, New York, 1998.