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Three Dimensional Electromagnetic Sub-Surface Sensing by means of a Multi-Step SVM-Based Classification Technique

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Introduction

The detection of buried objects is a problem of great interest in civil, military, and humanitarian applications [1]. Towards this purpose, several inverse scattering approaches have been proposed in recent years. Usually, such techniques consider two-dimensional (*2D*) approximations in order to reduce the computational burden of the inversion process. Although two-dimensional algorithms proved useful in modeling simplified working conditions, dealing with realistic scenarios often requires full three-dimensional formulations that imply a very expensive processing for allowing a suitable resolution accuracy in the reconstruction. Such a drawback causes some limitations and generally interferes with the use of inverse scattering approaches especially when dealing with real-time applications.

On the other hand, some Learning-by-Examples (*LBE*) methods have been proposed for the on-line sub-surface detection and sensing of subsurface scatterers [2]-[4]. In such a framework, some promising (in terms of both computational saving and reliability), but preliminary, results have been obtained by reformulating the subsurface sensing problem into a classification one [5][6].

In this paper, the classification approach is extended from *2D* to the three-dimensional (*3D*) case carefully addressing the increased complexity issue by means of an effective multi-step strategy. As a matter of fact, by iteratively processing the training dataset (without requiring an extra amount of measurements), the proposed method is aimed at improving the spatial resolution of the original classification technique [6] even though dealing with a more complex problem. The effectiveness of the proposed approach has been preliminary assessed through a set of numerical experiments also in correspondence with blurred data and some representative results are shown in the following.

Mathematical Formulation

The *3D* geometry of the problem in hand is pictorially schematized in Fig. 1. A set of unknown objects belong to an investigation domain *D* (L_D-sided) buried in an inaccessible soil characterized by a relative dielectric permittivity ε_b and a conductivity σ_b. Such a scenario is illumined by a probing electromagnetic field $\underline{E}_{inc}$ generated by a set of *T* electromagnetic sources located above the air-soil interface at a distance d_t

from the surface. Starting from the knowledge of the scattered field $\underline{E}_{scatt}$ collected at *M* positions ($\underline{r}_m, m = 1,..., M$) on a horizontal plane *h* far from the surface, the detection problem (or "*quantitative sensing*") is recast as that of finding a map of the "*occupancy*"-probability of the investigation domain. Towards this aim, *D* is partitioned in a three-dimensional lattice of *N* cuboids. The state χ_n of the *n*-th cuboid can be either empty (if any scatterer belongs to it), $\chi_n = -1$, or occupied, $\chi_n = 1$.

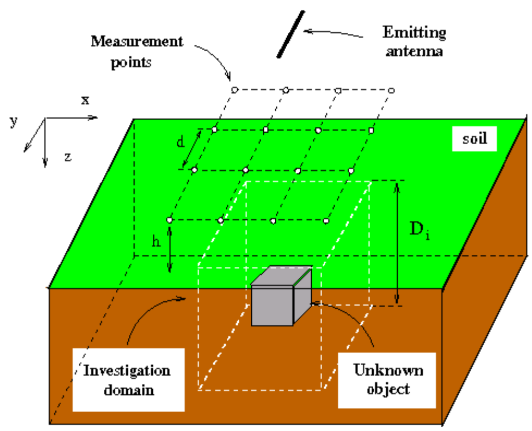

Fig. 1 - Three-dimensional subsurface scenario.

Accordingly, the problem can be mathematically formulated as follows: "*determining the probability array* $\underline{Q} = \{q_n; n = 1,..., N\}$ *from the scattering data* $\underline{\Gamma}_E$", $q_n = \Pr\{\chi_n = 1 | \underline{\Gamma}_E\}$ being the probability that the *n*-th cell is occupied and $\underline{\Gamma}_E = \left\{\underline{E}^{(t)}_{scat}(\underline{r}_m); m = 1,..., M; t = 1,..., T\right\}$. Such a statement defines a classification problem that can be profitably solved by means of a *SVM*-based [7] approach starting from the knowledge of a set of known examples (i.e., input-output relations $S = \left\{\left(\underline{\Gamma}_E, n, \chi_n; n = 1,..., N\right)^{(e)}; e = 1,..., E\right\}$ called "*training set*", *E* being the number of training examples). Moreover in order to achieve a suitable three-dimensional resolution, limiting the complexity of the classifier architecture, a multi-step strategy is used and summarized in the following [see also Fig. 2].

Step 0 – *Initialization.* The initialization step (s = 0) is aimed at obtaining a "*coarse*" (i.e., with a homogeneous spatial resolution, $r = 1$) probability map $\underline{Q} = \{q_n, n = 1, ..., N\}$ in the whole investigation area according to the two-stage [i.e., (*i*) definition of the decision function and (*ii*) mapping of the decision function into the *a-posteriori* probability] procedure detailed in [6];

Step 1 – *Identification of the Regions of Interest* (*ROIs*). This step is aimed at identifying the *ROI*s, to which the objects belong and where the spatial resolution will be enhanced. Towards this end, the map obtained at the previous step is binarized by thresholding. The resulting map is raster scanned from left- to right- hand side and from the top to bottom for detecting and dimensioning the *ROI*s;

Step 2 – *Zooming.* A synthetic zooming is performed only in the selected *ROI*s by using the same *SVM* architecture and data (*S*) used to obtain the coarse risk map at the *Step 0*. Accordingly, a multi-resolution probability map is defined

$$\underline{Q}^{(l)} = \left\{ q_{n_{(l)}} ; n_{(l)} = 1, \ldots, N_{(l)} ; l = 1, \ldots, L \right\} \tag{1}$$

being $N_{(l)} = N$ and where $q_{n_{(l)}}$ denotes the probability that an object or its part occupies the *n*-th cuboid at the *l*-th resolution level;

Step 3 – Go to "*Step 1*" ($s \leftarrow s+1$) until a "*stationary condition*" on the dimensions of the *ROI*s between two consecutive steps (s and s-1) holds true.

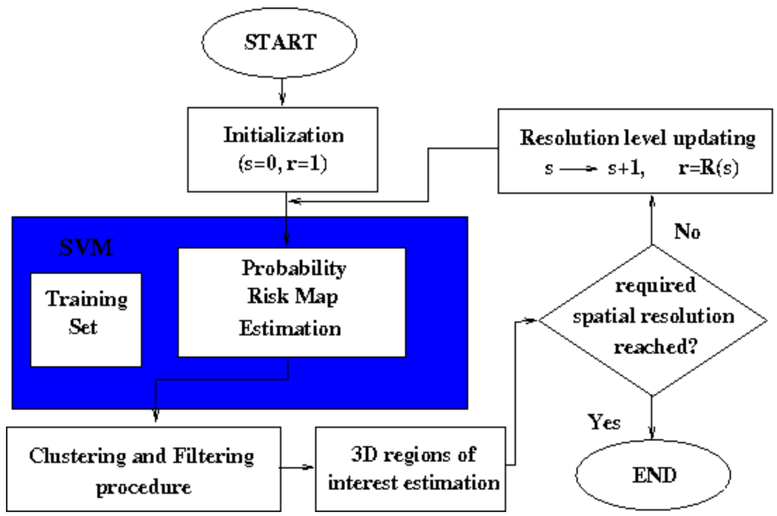

Fig. 2 - *SVM*-based multi-step sensing process.

Numerical Results

For the numerical assessment, an exhaustive set of experiments has been carried out and the following test case will be discussed here as a representative example of the behavior of the proposed approach. A dielectric scatterer ($\varepsilon_s = 10.0$, $\sigma_s = 0.0$) located at ($x_c = y_c = 0.0$, $z_c = -\lambda$) occupies a volume of dimension $\lambda/2 \times \lambda/2 \times \lambda/2$ in the investigation domain ($L_D = 2.0\lambda$) buried in a dry soil ($\varepsilon_b = 4.0$, $\sigma_b = 0.0$). A centered dipole ($T = 1$) illuminated such a scenario and $M = 16$ measurements points have been placed in the two-dimensional lattice above ($h = 0.1\lambda$) the soil surface (Fig. 1). The training dataset *S* of dimension $E = 100$ has been synthetically-generated with a *FEM 3D* electromagnetic simulator and by considering different positions in *D* of the scatterer. As far as the test is concerned, the scattering data have been blurred by adding a Gaussian noise ($SNR = 30\,dB$). Moreover, at each step *s* of the multi-step procedure, the *ROI* has been partitioned in $N_{(l)} = 4 \times 4 \times 4$ equal cuboids.

As an example, the result reached at the final step ($s = S_{opt} = 2$) of the multi-step process is shown in Fig. 3. As it can be observed, the proposed approach allows a satisfactory detection and location of the volume of the actual scatterer. The estimated *ROI* (i.e., where the value of the probability is higher) occupies a large subset of the shape of the actual object.

Finally, concerning the computational issue, it should be pointed out that, neglecting the training procedure (carried out once and off-line), the *SVM*–based multi-step technique has been completed in less than one second.

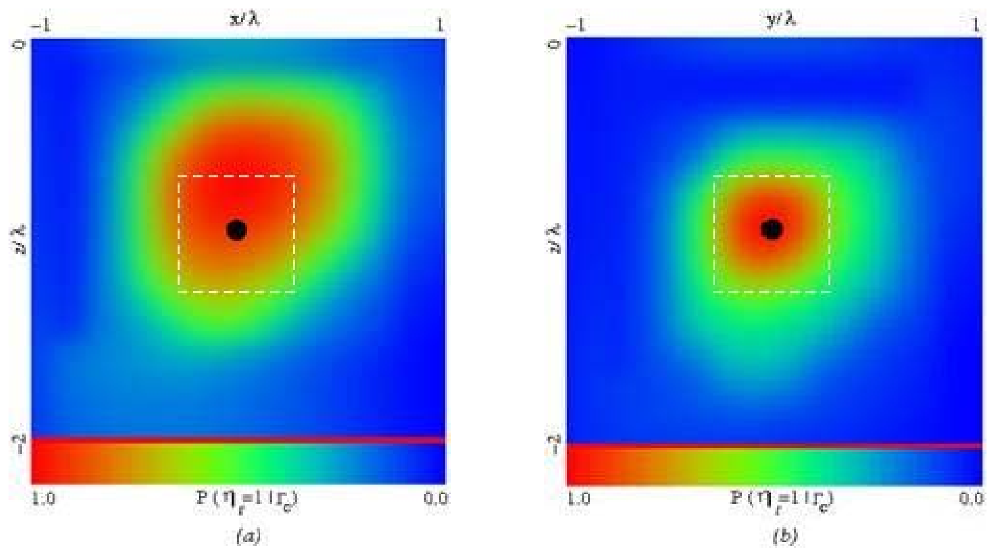

Fig. 3 – Slices of the estimated "occupancy" probability map at (*a*) $x = 0.0$ and (*b*) $y = 0.0$.

Conclusions

In this work, a classification approach for three-dimensional subsurface sensing has been presented. The approach is based on a *SVM*-based classification algorithm for defining an occupancy map of the area under investigation. In order to deal with *3D* scenarios, allowing a suitable spatial resolution without adding further measurements or processing, the algorithm has been integrated into a multi-step zooming procedure. The potentialities of the proposed approach have been assessed by means of a numerical validation with blurred synthetic data. Although preliminary, the obtained results suggest that an extension to real on-line *3D* cases is worth to be pursued.

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