An Innovative Real-Time Technique for Buried Object Detection

Emanuela Bermani, Andrea Boni, Salvatore Caorsi, *Associate Member, IEEE*, and Andrea Massa, *Member, IEEE*

***Abstract*—In this letter, a new online inverse scattering methodology is proposed. The original problem is recast into a regression estimation one and successively solved by means of a support vector machine (SVM). Although the approach can be applied to various inverse scattering applications, it results very suitable to deal with the buried object detection. The application of SVMs to the solution of such kind of problems is firstly illustrated. Then, some examples, concerning the localization of a given object from scattered field data acquired at a number of measurement points, are presented. The effectiveness of the SVM method is evaluated also in comparison with classical neural networks based approaches.**

***Index Terms*—Buried objects, inverse scattering problems, real-time detection, support vector machines.**

I. Introduction

The solution of inverse scattering problems is usually very difficult due to their inherent non linear nature and ill-posedness. Nowadays, the leading way to face them is to recast the original problem into an optimization one, which is successively solved by means of a minimization technique (e.g., see [1]–[3] and the reference therein). Unfortunately, the use of iterative procedures often makes the reconstruction process computationally expensive. As a consequence, serial implementations of optimization techniques cannot be generally used for real-time applications.

Therefore, the development of alternative strategies, when online reconstructions are required (i.e., industrial process control, leak detection, materials characterization during manufacturing and while in use, landmine detection, etc.) is mandatory. Recently, a great attention has been devoted to inverse scattering methodologies based on neural networks (NNs). Methods based on both multilayer perceptron (MLP) [4], [5] and radial basis function (RBF) [6] NNs have been successfully proposed.

However, in spite of their success, NN-based approaches suffer from typical problems of neural networks (e.g., the overfitting, etc.) which make the method accuracy highly *training dependent*. A solution to these problems is the use of RBF-based techniques trained with orthogonal least squares [7].

In this letter, the effectiveness of an alternative procedure, based on a support vector machine [8], is presented. SVMs are built on a solid theoretical framework, the statistical learning theory (SLT) [9]. Similarly to NNs, (after the training phase) the SVM allows to obtain reconstruction results in quasi real time (few tenths of seconds), with a percentage of time saved with respect to iterative methods greater than 90% [10], [11]. Moreover, SVM-based procedures allow the control of the generalization accuracy of the approximating function. More in detail, the arising optimization problem is aimed at finding the best trade-off between the capability of the SVM to learn from the given set of examples and a measure of the complexity of the model itself. Since the model complexity has a straightforward consequence on the generalization accuracy [9], this leads to the determination of models that outperform standard NNs.

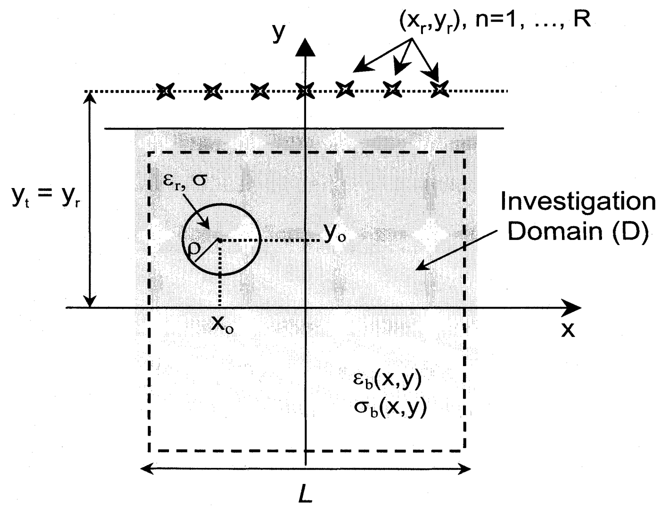

Fig. 1. Problem geometry.

In the following, a brief description of the electromagnetic problem and of the basic theory of the support vector machine will be presented (Sections II and III, respectively). In Section IV, the performances of the proposed SVM-based inverse scattering technique will be assessed and compared with those obtained with a NN-based approach by considering the localization problem. In particular, the attention will be focused on the localization of a cylindrical geometry with circular cross section. This problem is largely encountered in practical applications as, for example, the detection of buried pipes, tubes, or cables in urban environments. Finally some conclusions and final remarks will be provided.

II. Mathematical Formulation

Let us consider the two-dimensional half-space problem shown in Fig. 1. A homogeneous pipe is buried in a lossy region

Manuscript received April 15, 2002; revised January 29, 2003.

E. Bermani, A. Boni, and A. Massa are with the Department of Information and Communication Technology, University of Trento, Trento I-38050, Italy (e-mail: andrea.massa@ing.unitn.it).

S. Caorsi is with the Department of Electronics, University of Pavia, Pavia I-27100, Italy.

Digital Object Identifier 10.1109/TGRS.2003.810928

with relative dielectric parameters, generally inhomogeneous, $\varepsilon_b(x, y)$ and $\sigma_b(x, y)$. The unknown homogeneous scatterer is characterized by constant permittivity ε_r and conductivity σ values. The geometric characteristics (position, shape, and size) of the scatterer are defined by the center coordinates, (x_0, y_0), and by the parametric description of its cross section given by

$$x = x_0 + \rho\cos\theta \quad y = y_0 + \rho\sin\theta, \qquad 0 \le \theta < 2\pi. \quad (1)$$

For computational purposes, let us assume a square investigation domain (D) large enough (L-sided) so that the scatterer lies in D. Multiple illuminating sources and measurement points are located above or on the air–ground interface at the same height $(y_t = y_r)$. When the electric source is a line source, located at (x_t, y_t) and radiating a monochromatic electromagnetic field, the electric field scattered by buried targets and collected at the observation points, (x_r, y_r), $r = 1, \ldots, R$, is expressed as

$$\begin{aligned} &E^{\text{scatt}}(x_r, y_r|x_t, y_t) \\ &\quad = E_b^{\text{scatt}}(x_r, y_r|x_t, y_t) + k^2 \int_D E_b(x, y|x_t, y_t) \\ &\qquad \cdot G(x_r, y_r; x, y)\, O\{(x, y)|x_0, y_0, \rho, \varepsilon_r, \sigma\}\, dx\, dy \quad (2)\end{aligned}$$

where E^{scatt} and E_b^{scatt} are the scattered electric fields at the measurement points when the reconstruction domain contains or not the unknown scatterer, respectively; E_b is the electric field inside the reconstruction domain filled with the background medium; G is the Green's function of the inhomogeneous medium [12]; and $O(x, y)$ is the relative dielectric profile defined as follows

$$O(x, y) = \begin{cases} \varepsilon_r - \varepsilon_b(x, y) - j\,\dfrac{\sigma - \sigma_b(x, y)}{2\pi f}, \\ \qquad\qquad \text{if } \sqrt{(x - x_0)^2 + (x - y_0)^2} \le \rho \\ 0, \qquad \text{otherwise.} \end{cases} \quad (3)$$

Inverse scattering procedures aim at retrieving the location, the shape, and the dielectric properties of the scatterer starting from the knowledge of $E^{\text{scatt}}(x_r, y_r|x_t, y_t)$. Mathematically, the problem reduces to determine the following relation:

$$\underline{\chi} = \Phi\left\{\underline{E^{\text{scatt}}}\right\} \quad (4)$$

where $\underline{\chi}$ is the scatterer array ($\underline{\chi} = [\chi_i; i = 1, \ldots, P] = [x_0, y_0, \rho, \varepsilon_r, \sigma]$ being P the number of parameters which completely describe the scatterer), and $\underline{E^{\text{scatt}}}$ is the data array defined as $\underline{E^{\text{scatt}}} = [E^{\text{scatt}}(x_r, y_r|x_t, y_t);\ r = 1, \ldots, R;\ t = 1, \ldots, T]$. This problem can be reformulated as a *regression problem*, where the unknown function (Φ) must be approximated from the knowledge of a number of known I/O pairs of vectors $\{(\underline{\chi})_n, (\underline{E^{\text{scatt}}})_n\}; n = 1, \ldots, N$.

III. SVM-Based Inverse Scattering Procedure

Generally speaking, a regression problem is the process through which an unknown function $\Phi : \Re^{2R\times T} \rightarrow \Re$ is approximated by means of a function $\tilde{\Phi}$ on the basis of some samples $\{(\underline{\upsilon}_n, e_n)\}_{n=1,\ldots,N}$, $\underline{\upsilon}_n$ being an input pattern and e_n the corresponding target ($e_n = \Phi\{\underline{\upsilon}_n\}$). As far as buried-object detection problems are concerned, the location (x_0, y_0), the dimension (ρ), and the complex permittivity (ε_r, σ) of the scatterer must be retrieved and each unknown parameter is dealt with separately. Consequently, $\underline{\upsilon}_n = (\underline{E^{\text{scatt}}})_n$ and $e_n = (\chi_i)_n$.

Usually, a problem is formulated as a regression one when it is possible to observe and to measure the I/O signals of the system under test, but the system dynamic is unknown (i.e., an analytic expression for Φ is not available). SVMs are a new paradigm that have been recently proposed for the solution of pattern recognition and function approximation tasks. Briefly (the reader can refer to [8] for more details), the SVM-based procedure aims at finding a smooth function $\tilde{\Phi}$ having at most ϵ deviation from the targets e_n for all samples. The function $\tilde{\Phi}$ is given by

$$\tilde{\Phi}(\underline{\upsilon}) = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) k(\underline{\upsilon}_n, \underline{\upsilon}) + b \quad (5)$$

where k is a kernel function, while functional parameters $(\underline{\alpha}, \underline{\alpha}^*, b)$ and *structural parameters* (ϵ, C, σ^2) are unknown quantities. The parameter C measures the trade-off between the capability of $\hat{\Phi}(\underline{\nu})$ to approximate the input samples and the error on the new samples [8], while σ^2 is the variance of the kernel function, when Gaussian functions are taken into account. It is important to note that expression (5) has the same form as for RBF approaches. As a matter of fact, Gaussian SVMs can be view as a special case of standard RBF networks [13] whose centers and weights are computed following a different procedure, as detailed later on.

The arrays $\underline{\alpha}$ and $\underline{\alpha}^*$ in (5) are computed by solving the following constrained quadratic programming problem (CQP)

$$\min_{\underline{\beta}} \left\{\tfrac{1}{2}\,\underline{\beta}^T Q \underline{\beta} + \underline{r}^T \underline{\beta}\right\} \quad (6)$$

subjected to the constraints $0 \le \beta_n \le C, \forall n = 1, \ldots, 2N$ and $\underline{\beta}^T \underline{t} = 0$, being

$$Q = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix} \qquad \underline{\beta} = \begin{bmatrix} \underline{\alpha} \\ \underline{\alpha}^* \end{bmatrix}$$
$$\underline{r} = \begin{bmatrix} \underline{\epsilon} - \underline{e} \\ \underline{\epsilon} + \underline{e} \end{bmatrix} \qquad \underline{t} = \begin{bmatrix} \underline{1} \\ -\underline{1} \end{bmatrix} \quad (7)$$

and $k_{ij} = k_{ji} = k(\underline{\upsilon}_i, \underline{\upsilon}_j)$, $\epsilon_i = \epsilon, \forall i$; $\dim(Q) = 2N \times 2N$; $\dim(\underline{\beta}) = \dim(\underline{r}) = \dim(\underline{t}) = 2N$. The structure of the optimization problem (6) is a key point of the proposed approach. Its solution is the global minimum of the arising cost function, and the local minima problem, which affects classical back-propagation algorithms, is completely avoided. In order to solve (6), traditional optimization techniques can be used. To this end, a very effective procedure, described in [14], is adopted in this work.

The threshold b is computed by means of the Karush–Kuhn–Tucker (KKT) conditions of the CQP at optimality, while the *hyperparameters* of the problem are determined according to a model selection process (namely, the bootstrap procedure [15]) aimed at minimizing the control parameter h given by

$$h = R^2 \sum_{n,m} (\alpha_n - \alpha_n^*)(\alpha_m - \alpha_m^*) k(\underline{\nu}_n, \underline{\nu}) \tag{8}$$

R being the radius of the smaller hypersphere containing all the training data [9].

IV. Numerical Results

In order to assess the effectiveness of the proposed approach, numerical simulations and comparisons with a MLP NN-based procedure [16] have been performed.

The geometry under test is illuminated by means of an electric line source located $\lambda_0/6$ above the air–soil interface. This source model avoids the drawbacks arising from the modeling of complex electromagnetic sources. Consequently, the attention is focused on the assessment of the proposed procedure. Moreover, the electric line source is a simplified model of realistic antennas when two-dimensional problems are addressed. A buried lossless ($\varepsilon_r = 5.0$) circular ($\rho = \lambda_0/12$) cylinder lies into the domain D. The dielectric parameters characterizing the subsurface region are $\varepsilon_b = 20.0$ and $\sigma_b = 10^{-2}$ S/m and represent a worse case with respect to the realistic soil [18]. The investigation area is a square region $L = \lambda_0$-sided, λ_0 being the wavelength in the upper region and the order of magnitude of the skin depth [18]. The scattered data at each measurement point are synthetically computed by using a finite-element code and a PML truncation technique [19]. For an accurate representation of the scattered electric field [17], 16 equally spaced ($\lambda_0/15$) measurement points are arranged on a line placed in region 1 at $y_t = y_r = (2/3)\,\lambda_0$ (Fig. 1).

Let us consider the localization problem. For comparison purposes, a two-layer MLP, characterized by 32 input, 32 hidden, and two output neurons (previously proposed and assessed in [16]), is firstly trained by considering a standard back-propagation algorithm. In the "learning phase," a dataset of 700 examples, synthetically computed by uniformly varying the position of the scatterer inside D ($x_{n,\,\mathrm{train}} = -(\lambda_0/2) + n\Delta x$, $n = 0, 1, \ldots, 9$, $\Delta x = 0.112\lambda_0$, $y_{n,\,\mathrm{train}} = -(\lambda_0/2) + m\Delta y$, $m = 0, 1, \ldots, 7$, $\Delta y = 0.167\lambda_0$) is considered. As shown in [16], 700 equally distributed examples define a suitable set to train NN for the solution of localization problems. Input data for the NN are the real and the imaginary parts of the scattered field collected at the measurement line. The center-coordinated x_0 and y_0 are the NNs outputs.

In order to compare NN and SVM performances under the same "conditions," the same training set has been considered during the SVM learning phase. However, since SVMs have been developed to solve one-output learning problems (see [9] for further details), two different SVMs, one for each coordinate of the target, are trained by using the CQP algorithm. Gaussian functions are considered as kernel functions due to their capability to work as a universal approximator [13]. After the bootstrap procedure, the values of the hyperparameters result: $(\sigma^2)_{x_0} = 0.12$, $(\sigma^2)_{y_0} = 0.1$, $(C)_{x_0} = 1280$, $(C)_{y_0} = 5120$, and $\epsilon = 0.001$.

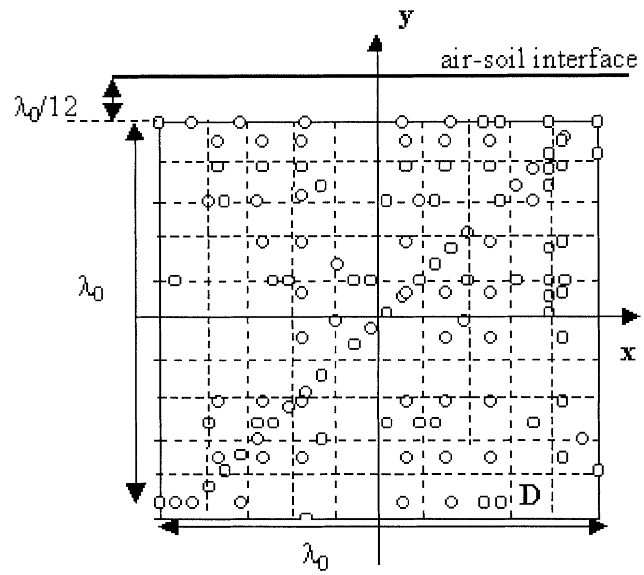

Fig. 2. Test case.

The performances of the classical NN- and SVM-based procedures are illustrated and compared in the following by considering first a noiseless test set made up of 160 examples. These examples are synthetically obtained by randomly varying the position of the cylinder inside D. The cylinder locations are different from those of the training set (Fig. 2). Figs. 3 and 4 show the estimated versus the actual scatterer properties when the SVM- and NN-based approaches are taken into account, respectively. Both actual and estimated values are normalized to the maximum admissible error Λ (set equal to the investigation domain side, $\Lambda = \lambda_0$). Let us observe that, as far as the scatterer depth estimation is concerned, SVM greatly reduces the error of the NN, and the correlation coefficient ($\Omega_y = y_{0,\,\mathrm{act}}/y_{0,\,\mathrm{est}}$, where the subscripts act and est indicate the actual and estimated values, respectively) results much closer to one. Such an improvement is mainly due to the definition of the kernel deviation ϵ that guarantees targets to deviate at most ϵ from the function itself. Moreover, larger errors occur when the targets are positioned just below the air–ground interface. This is probably due to the interaction between the object and the interface, and it is more evident when targets are positioned near the left and right side of the investigation domain.

In order to quantitatively evaluate the localization accuracy, let us define some error figures

$$\xi_x = \frac{|x_{0,\,\mathrm{act}} - x_{0,\,\mathrm{est}}|}{\Lambda} \tag{9}$$

$$\xi_y = \frac{|y_{0,\,\mathrm{act}} - y_{0,\,\mathrm{est}}|}{\Lambda}. \tag{10}$$

Fig. 5 shows the mean value and the variance for both the error figures when the NN and the SVM are used. As expected, SVM enhances the performances achieved with the standard NN approach due to optimal generalization properties guaranteed from the SLT.

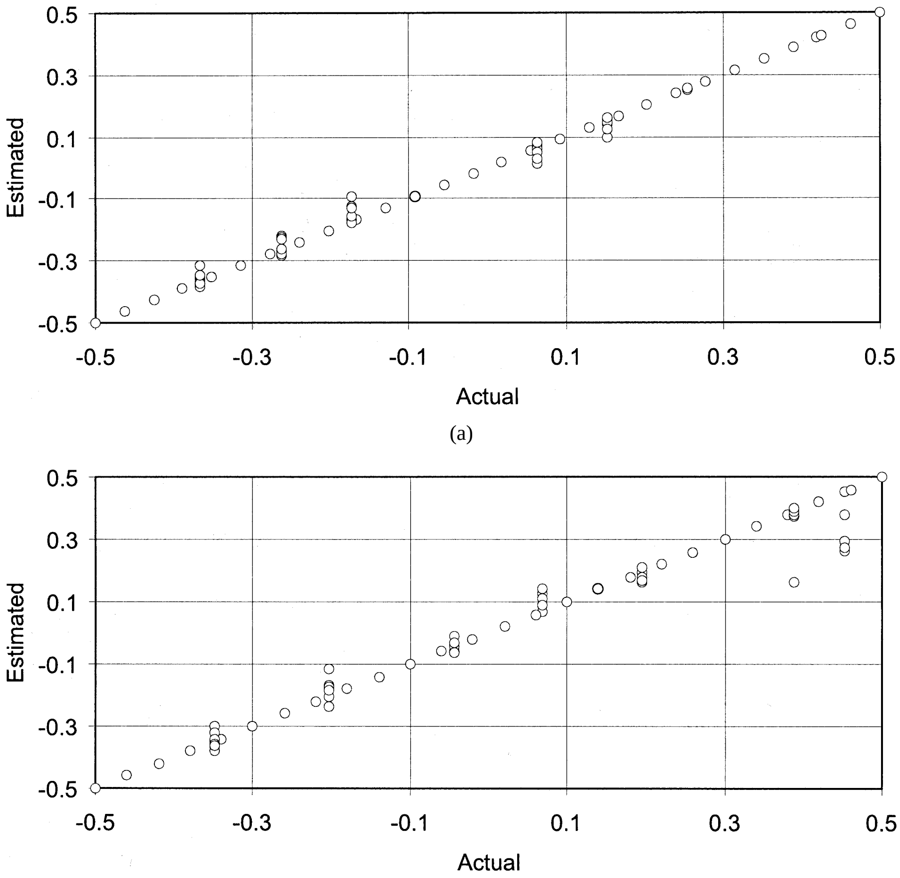

Fig. 3. SVM-based approach. Estimated versus real scatterer properties. (a) x_0/λ_0 and (b) y_0/λ_0.

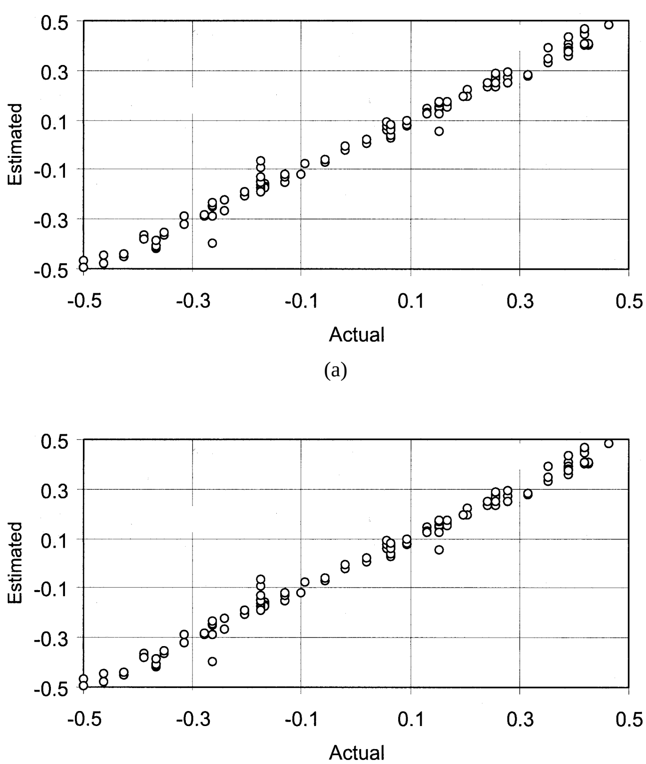

Fig. 4. NN-based approach. Estimated versus real scatterer properties. (a) x_0/λ_0 and (b) y_0/λ_0.

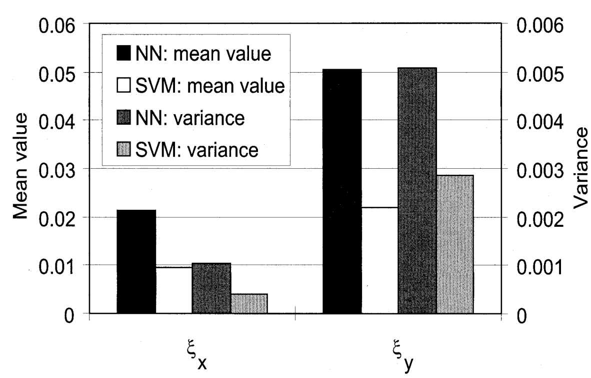

Fig. 5. SVM-based approach versus NN-based approach. Location error: standard deviation and average values.

In order to analyze the robustness of the proposed approach, target objects of circular cross section, with radii and dielectric permittivities different from those of the training set, have also been taken into account. First, different locations of the target in D have been considered ($x_0 = 0$, $y_0 \in [0; 028\lambda_0]$). In correspondence with radius variations, the mean values of the error figures are $\langle \xi_x \rangle_{\rm SVM} = 0.022$, $\langle \xi_y \rangle_{\rm SVM} = 0.12$, and $\langle \xi_x \rangle_{\rm NN} = 0.095$, $\langle \xi_y \rangle_{\rm NN} = 0.31$, respectively. Similar results have been obtained also when the SVM approach is adopted for localizing objects with different values of permittivity. The values of the average error are equal to $\langle \xi_x \rangle_{\rm SVM} = 0.017$ and $\langle \xi_y \rangle_{\rm SVM} = 0.10$. For the same test set, the results achieved by using the NN technique are $\langle \xi_x \rangle_{\rm NN} = 0.045$ and $\langle \xi_y \rangle_{\rm NN} = 0.14$.

TABLE I
NOISY MEASUREMENT DATA. AVERAGE VALUES. (a) ξ_x AND (b) ξ_y FOR DIFFERENT SIGNAL-TO-NOISE RATIOS (SNRs)

SNR [dB]	50	35	20	10	5
SVM	0.017	0.019	0.036	0.080	0.130
NN	0.035	0.053	0.110	0.210	0.270

(a)

SNR [dB]	50	35	20	10	5
SVM	0.058	0.060	0.070	0.130	0.170
NN	0.100	0.110	0.220	0.350	0.350

(b)

Moreover, the dependence of the localization accuracy versus the target shape has been analyzed. To this aim, the target is a cylinder with square cross section. The area of the cylinder is the same of the reference circular cylinder used in the training phase. The achieved average localization errors ($\langle\xi_x\rangle_{\mathrm{SVM}} = 0.021$ and $\langle\xi_y\rangle_{\mathrm{SVM}} = 0.09$) confirm the generalization capability of the SVM and the effectiveness of the proposed approach with respect to the NN technique ($\langle\xi_x\rangle_{\mathrm{NN}} = 0.12$ and $\langle\xi_y\rangle_{\mathrm{NN}} = 0.39$).

Finally, a noisy environment has been considered. Noisy data have been obtained by adding a uniform Gaussian noise to simulated measurement data. The obtained results are given in Table I.

V. CONCLUSION

In this letter, an innovative online inverse scattering methodology, based on the implementation of a support vector machine, has been presented and applied to the detection of buried objects. The training of SVM requires the solution of a constrained quadratic optimization problem. This is a key point of the proposed approach, and it represents the main advantage of the method (with respect to MLP NN-based procedures). It avoids typical drawbacks as overfitting or local minima occurrence.

The effectiveness of the proposed approach has been checked by considering the localization of a given target. An exhaustive numerical analysis has been performed and selected numerical results (statistically significant) have been presented in order to assess the robustness of the method. The obtained results clearly demonstrated significant improvements in the quasi-real-time localization of pipes buried in inaccessible domains. Moreover, the generalization capability of the SVM procedure has been also pointed out. Future works, currently under development, will be devoted to further assess the method and to introduce, in a convenient way, some *a priori* information into the retrieval procedure.

REFERENCES

[1] K. Belkebir, R. E. Kleinman, and C. Pichot, "Microwave imaging— Location and shape reconstruction from multifrequency scattering data," *IEEE Trans. Microwave Theory Tech.*, vol. 45, pp. 469–476, Apr. 1997.

[2] H. Harada, D. J. N. Wall, T. Takenaka, and M. Tanaka, "Conjugate gradient method applied to inverse scattering problem," *IEEE Trans. Antennas Propagat.*, vol. 43, pp. 784–792, Aug. 1995.

[3] S. Caorsi, A. Massa, and M. Pastorino, "A computational technique based on a real-coded genetic algorithm for microwave imaging purposes," *IEEE Trans. Geosci. Remote Sensing*, vol. 38, pp. 1697–1708, July 2000.

[4] S. Caorsi and P. Gamba, "Electromagnetic detection of dielectric cylinders by a neural network approach," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 820–827, Mar. 1999.

[5] R. Mydur and K. A. Michalski, "A neural-network approach to the electromagnetic imaging of elliptic conducting cylinders," *Microwave Opt. Technol. Lett.*, vol. 28, pp. 303–306, Mar. 2001.

[6] I. T. Rekanos, "On-line inverse scattering of conducting cylinders using radial basis-functions neural networks," *Microwave Opt. Technol. Lett.*, vol. 28, pp. 378–380, Mar. 2001.

[7] ——, "Inverse scattering of dielectric cylinders by using radial basis function neural networks," *Radio Sci.*, vol. 36, pp. 841–849, Sept.–Oct. 2001.

[8] N. Cristianini and J. S. Taylor, *An Introduction to Support Vector Machines*. Cambridge, U.K.: Cambridge Univ. Press, 2000.

[9] V. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.

[10] N. V. Budko and P. van den Berg, "Characterization of a two-dimensional subsurface object with an effective scattering model," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 2585–2596, Sept. 1999.

[11] T. J. Cui, W. C. Chew, A. A. Aydiner, and S. Chen, "Inverse scattering of two-dimensional dielectric objects buried in a lossy hearth using the distorted Born iterative method," *IEEE Trans. Geosci. Remote Sensing*, vol. 39, pp. 339–346, Feb. 2001.

[12] S. Caorsi, G. L. Gragnani, and M. Pastorino, "Numerical electromagnetic inverse-scattering solutions for two-dimensional infinite dielectric cylinders buried in a lossy half-space," *IEEE Trans. Microwave Theory Tech.*, vol. 41, pp. 352–356, Feb. 1993.

[13] C. Christoloulou and M. Georgiopoulos, *Applications of Neural Networks in Electromagnetics*. Norwood, MA: Artech House, 2001.

[14] J. Platt, "Fast training of support vector machines using sequential minimal optimization," in *Advances in Kernel Methods—Support Vector Learning*, B. Scolkopf, C. Burges, and A. Smola, Eds. Cambridge, MA: MIT Press, 1999.

[15] D. Anguita, A. Boni, and S. Ridella, "Evaluating the generalization ability of support vector machines through the bootstrap," *Neural Process. Lett.*, vol. 11, pp. 1–8, Feb. 2000.

[16] E. Bermani, S. Caorsi, and M. Raffetto, "An inverse scattering approach based on a neural network technique for the detection of dielectric cylinders buried in a lossy half-space," in *Progress in Electromagnetic Research*, 2000, vol. PIER 26, pp. 69–90.

[17] E. Bermani, S. Caorsi, A. Massa, and M. Raffetto, "On the training patterns of a neural network for inverse scattering problems in the spatial domain," *Microwave Opt. Technol. Lett.*, vol. 28, pp. 207–209, Feb. 2001.

[18] U. Oguz and L. Gurel, "Frequency responses of ground penetrating radars operating over highly lossy grounds," *IEEE Trans. Geosci. Remote Sensing*, vol. 40, pp. 1385–1394, June 2002.

[19] S. Caorsi and M. Raffetto, "Perfectly matched layers for the truncation of finite element meshes in layered half-space geometries and applications to electromagnetic scattering by buried objects," *Microwave Opt. Technol. Lett.*, vol. 19, pp. 427–434, Dec. 1998.