Progress In Electromagnetics Research Letters, Vol. 23, 119–128, 2011

THE SUPPORT VECTOR MACHINE FOR DIELECTRIC TARGET DETECTION THROUGH A WALL

F.-F. Wang and Y.-R. Zhang

School of Electronic Science and Engineering
Nanjing University of Posts and Telecommunications, Nanjing, China

Abstract—In this paper, a novel approach based on the support vector machine (SVM) for dielectric target detection in through-wall scenario is proposed. Through-wall detection is converted to the establishment and use of a mapping between backscattered data and the dielectric parameter of the target. Then the propagation effects caused by walls, such as refraction and speed change, are included in the mapping that can be regressed after SVM training process. The training and testing data for the SVM is obtained by finite-difference time-domain (FDTD) simulation. Numerical experiments show that once the training phase is completed, this technique only needs computational time in an order of seconds to predict the parameters. Besides, experimental results show that good consistency between the actual parameters and estimated ones is achieved. Through-wall target tracking is also discussed and the results are acceptable.

1. INTRODUCTION

Sensing through obstacles, such as walls, doors, and other visually opaque materials using microwave signals, is emerging as a powerful tool which supports a range of civilian and military applications [1, 2]. Through-the-wall radar imaging (TWRI) has been recently sought out for surveillance and reconnaissance in urban environments, which can be employed to detect and locate survivors for the succors in search and rescue in natural disasters, such as earthquakes and avalanches.

In through-wall applications, it is necessary to determine the shape, location and physical properties of the target located at the other side of a wall in order to track their motion, based on the knowledge about the scattered field from the target. The propagation

Received 11 March 2011, Accepted 26 April 2011, Scheduled 29 April 2011
Corresponding author: Fang-Fang Wang (fangfangwang819@163.com).

effects of walls are not incorporation into the conventional imaging technology such as synthetic aperture radar (SAR) techniques [2]. Ahmad et al. and Wang and Amin [3–6] proposed a geometric method in which the refraction path is obtained using Snell theorem. Then the approach compensates this effect in an imaging algorithm with wideband synthetic beamforming. Although this technique is successful for the target location estimation in through-the-wall radar imaging applications, the multiple interactions between walls and the target or between wall's surfaces are not taken into consideration, which typically occur in through-wall imaging (TWI) scenarios. Besides, only the location of the target can be detected with this method. Therefore, some numerical methods [7–11], by use of the differences in dielectric properties between the target and the surrounding environments, are applied to TWI for more accurate results. Among these approaches, the presence of walls is implicitly taken into account through the Green's function. Generally, these existing numerical algorithms for target identification can be divided into two kinds: one is based on the linear approximation such as Born approximation [7], and the other is based on the use of nonlinear optimization [8]. The former is only suitable for the weak scattering target, and the latter is often trapped into local minima, computationally expensive, and time consuming.

Integral equation (IE)-based modeling technique is usually employed in through-wall problem. The relationship between the scattered field and dielectric properties of the target are nonlinear according to the integral equation, which is difficult to be explicitly revealed in those existing numerical method based on integral equation (IE)-based modeling technique. In this paper, through-wall detection is converted to the establishment and use of a mapping between backscattered data and the dielectric parameter of the target. Providing the dielectric parameters of a target are given, the scattered field can be collected through finite-difference time-domain (FDTD) simulation. A pair which consists of one dielectric parameter and scattered field of the target is called training data (i.e., input-output measurement). Therefore, through-wall detection problem can be recast into a regression one with these training data. This technique is called learning-from-samples (LFS) technique. In this way, the effects caused by walls can be included in the mapping obtained after the training phase. Based on the mapping, the dielectric parameters of the target can be predicted from the backscattered field.

In this paper, we detect target through a wall with the support vector machine (SVM). SVM is one of the LFS techniques. SVM was originally designed for binary classification. Recently, it has been used for solving inverse problems extensively [12–15], which can be reformulated into regression ones [16, 17]. The SVM allows to obtain reconstruction results in quasi real time, with a percentage of time saved with respect to iterative methods greater than 90% [12]. In contrast to the conventional artificial neural networks (NN) [18, 19], SVM have a strong theoretical foundation (statistical learning theory) with well-defined generalization property and do not suffer from the curse of dimensionality. Moreover, another advantage of SVM is that unlike optimization problems arising from NN training, constrained quadratic optimization problem (CQP) in SVM has a unique solution, and hence does not suffer from local minima. Simulation results show that it is effective to estimate dielectric properties of the target in through-wall problem using SVM. In addition, the detection of the dielectric target moving along a circular orbit is simulated, and the predicted track is approximately consistent with the actual orbit.

This paper is organized as follows. In Section 2, the physical model of the problem is presented. In Section 3, the theory of SVM is introduced based on the model obtained in the above section. Section 4 assesses the performance of the proposed through-wall technique and experimental results are given. Finally, some conclusions and final remarks are provided.

2. PHYSICAL MODELLING

Let us consider a dielectric target inside a room. The room is illuminated by a transmitter TX emitting monochromatic electromagnetic wave; and the scattered field is collected by a receiver RX; both the transmitter and receiver are located at the same side of the walls.

As illustrated in Fig. 1, a state vector $\mathbf{y}$ represents the indoor target. Sensors (defined by a sensor state vector $\mathbf{p}$) collect the data vector $\mathbf{x}$ corresponding to the relevant information of the vector $\mathbf{y}$. In this paper, background subtraction is used to remove the wall reflection. Therefore, the vector $\mathbf{x}$ is the scattered filed from the

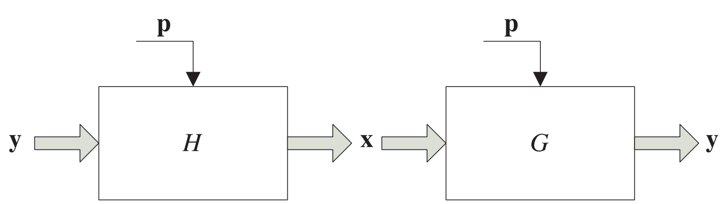

Figure 1. Physical model.

target. The relationship between vectors $\mathbf{x}$ and $\mathbf{y}$ can be expressed as a parameterized transfer function H

$$\mathbf{x} = H(\mathbf{p}, \mathbf{y}) \tag{1}$$

We attempt to find an approximate inverse transfer function $G(\mathbf{p})$

$$\mathbf{y} = G(\mathbf{p}, \mathbf{x}) \tag{2}$$

The through-wall problem is nonlinear and ill-posed. Generally, the approximate inverse $G(\mathbf{p})$is not unique. Consequently, we recast the TWI problem into a regression one, providing the training dataset is given $(\mathbf{x}_i, \mathbf{y}_i, i = 1, 2, 3, \ldots, l)$, where

$$\begin{aligned} \mathbf{x}_i &= (\mathbf{E}_{rs|ts},\, rs = 1, 2, 3, \ldots, R,\, ts = 1, 2, 3, \ldots, T) \\ \mathbf{y}_i &= (x_0, y_0, \rho, \varepsilon_r, \sigma) \end{aligned}$$

The target is centered at (x_0, y_0) with a diameter of ρ, and the conductivity and dielectric permittivity of scatterers are characterized by σ, ε_r respectively. $\mathbf{E}_{rs|ts}$ represents the scattered electric field measured at the rth receiving position (x_{rs}, y_{rs}) illuminated by the transmitter TX located at (x_{tr}, y_{tr}). Once the mapping from $\mathbf{x}$ to $\mathbf{y}$ is established, we can predict the vector $\mathbf{y}$ from the data vector $\mathbf{x}$, which is collected by receivers.

3. SUPPORT VECTOR REGRESSION

The training dataset $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l)\} \subset R^N \times R$ is given, where R^N denotes the space of the input patterns; $\mathbf{x}_i$ represents the scattered field due to the target, and y_i represents parameters of the scatterer such as position, shape, and the electromagnetic characteristic (i.e., y is an element of the vector $\mathbf{y}$).

Since the SVM can only predict one parameter at one time, the dielectric parameters such as relative permittivity and conductivity have their own mapping to the scattered data. Here we take $\mathbf{x}_n = (\mathbf{E}_{rs|ts})_n$, $y_n = (\varepsilon_r)_n$ as an example. We begin with describing the case of linear function f, which takes the form

$$y = G(\mathbf{p}, \mathbf{x}) = f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b = \mathbf{w} \cdot \mathbf{x} + b \quad \text{with} \quad \mathbf{w} \in R^N, \quad b \in R \tag{3}$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product in R^N, $\mathbf{w}$ and b are parameters obtained by minimizing the regression risk subject to some constrains. In the ε-SV regression, our goal is to find a function that has at most a deviation of ε from the actually obtained targets y_i for all the training data, and that is as flat as possible (ε is a constant number set in advance). The slack variables ξ_i and ξ_i^* are introduced for infeasible constraints for some acceptable errors. Therefore, the problem can be treated as an optimization issue as follows

$$\begin{aligned} &\min \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ &s.t. \quad \begin{cases} y_i - \langle \mathbf{w}, \mathbf{x}_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \mathbf{w}, \mathbf{x}_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned} \tag{4}$$

The constant $C > 0$ determines the trade-off between the flatness of f and the amount up to which deviation larger than ε is tolerated. If the differences between the actual and estimated values are larger than ε, the errors are the differences, otherwise the errors will be ignored. This corresponds to a so-called ε-insensitive loss function $c(f(\mathbf{x}) - y)$ described by

$$c(f(\mathbf{x}) - y) = \begin{cases} 0 & \text{if} \quad |f(\mathbf{x}) - y| \leq \varepsilon \\ |f(\mathbf{x}) - y| - \varepsilon & \text{otherwise} \end{cases} \tag{5}$$

Since the relationship between the scattered field and parameters of the target is nonlinear, it can be achieved by preprocessing the training pattern $\mathbf{x}_i$ via a transformation into some feature space F in which there are linear relation between scattered field and the parameter of the target:

$$\begin{aligned} \Phi : R^N &\rightarrow F \\ \mathbf{x} &\rightarrow \Phi(\mathbf{x}) \end{aligned}$$

The SVM algorithm depends on dot products between patterns $\mathbf{x}_i$, so only the information of kernel function $k(\mathbf{x}, \mathbf{x}') = \langle \Phi(\mathbf{x}), \Phi(\mathbf{x}') \rangle$, rather than that of Φ explicitly, is regarded for the simplification of the algorithm. To solve this optimization problem, we usually transform the primal problem to its dual one described as follows

$$\begin{aligned} &\text{maximize} \quad \begin{cases} -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)k(\mathbf{x}_i, \mathbf{x}_j) \\ -\varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \end{cases} \\ &\text{subject to} \quad \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \quad \text{and} \quad \alpha_i, \alpha_i^* \in [0, C] \end{aligned} \tag{6}$$

where Lagrange multipliers α and α^* are computed by solving the constrained quadratic programming problem (CQP). The function f is approximately given by $\tilde{f}$:

$$\tilde{f}(\mathbf{x}) = \sum_{n=1}^{N_{sv}}(\alpha_n - \alpha_n^*)k(\mathbf{x}_n, \mathbf{x}) + b \tag{7}$$

where $\mathbf{x}_n$ is a training pattern whose corresponding Lagrange multiplier is nonzero, such training patterns are called support vectors (SVs) and N_{sv} is the number of SVs. The process of establishing the mapping for the conductivity is the same as the one for relative permittivity.

4. EXPERIMENTAL RESULTS

In SVM regression, the kernel function is selected as the Gaussian kernel, which is given by

$$k(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2) \tag{8}$$

where γ is the variance of the kernel function which is determined using cross-validation in the training phase. The training and testing data for SVM is generated using FDTD simulation. The total dataset is achieved by repeated simulations with shift of the dielectric parameters such as relative permittivity and conductivity as follows

$$\begin{aligned} \varepsilon_r &= 1.5 + 0.25 * m, \quad m = 0, 1, \ldots, 14, \\ \sigma &= 10 \wedge (-3 + 0.05 * m), \quad m = 0, 1, 2, \ldots, 20 \end{aligned}$$

Then we randomly pick up 265 examples to get the training dataset and choose other examples as the testing dataset.

In this section, the direct electromagnetic scattering problem, which is exploited to collect data for SVM-based experimentation, is formulated. Fig. 2 shows the general scenario of an arbitrary dielectric scatterer residing in a simple room. The thickness of walls is 0.2 m. The investigation domain is $D = [-1.08, 1.08] \times [0.25, 3.64]\,\mathrm{m}^2$. The conductivity σ and relative permittivity ε_r of the walls are set as a standard value of 0.01 S/m and 8, respectively.

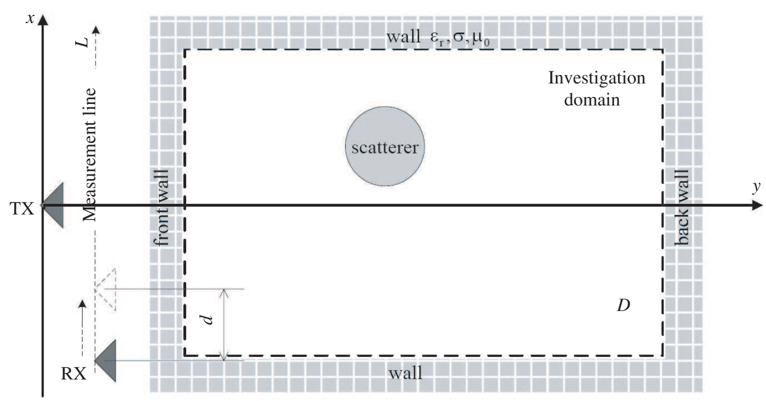

Figure 2. Room geometry.

The inside and outside regions of a room (i.e., walls are excluded) are free spaces with dielectric permittivity and magnetic permeability denoted by ε_0 and μ_0. The geometry of the room is discretized with the FDTD square cells of 1 cm length. The time resolution is 19.25×10^{-12} s. The transmitting antenna (TX) is fixed in the position of (0, 0) which is 0.05 m away from the front wall. The receiving antenna (RX) is 0.04 m away from the same side of the wall, which moves and synthesizes a measurement aperture $L = 2.4$ m. The positions of receiving antenna (RX) are distributed along the x-direction with coordinate $x_1 = -1.2$ m, $x_2 = -1.18$ m, $\ldots$, $x_{121} = 1.2$ m. To model the EM illumination of the modeled room and objects in it with an UWB short pulse, the transmitter dipole antenna is feed by a 4.5 ns Gaussian pulse modulated by a 0.5 GHz sine wave.

In order to assess the effectiveness of the proposed approach, numerical simulations have been performed. Fig. 3 displays the relationship between the actual and estimated dielectric properties including relative permittivity and conductivity of the target. All the circular marks in Fig. 3 are situated near the line $y = x$; SVM can predict the dielectric parameters with small errors in through-wall detection. The training time is 1422–1423 seconds. Once the training phase is completed, the proposed method requires only 9–10 seconds to predict the dielectric parameters. Moreover, the computation memory is 140512 KB. We also simulate a target to move along a circular orbit with the center at (1.0, 0) m and a radius of 0.5 m. The actual and estimated tracks are plotted in Fig. 4, the predicted track coincides with the actual one pretty well.

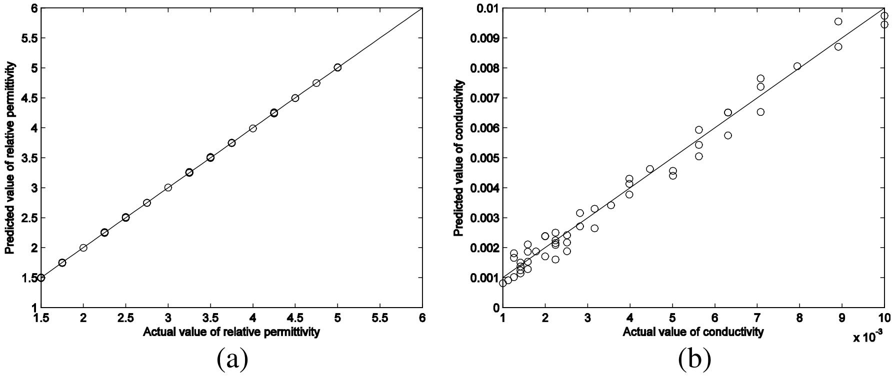

Figure 3. Predicted values of (a) relative permittivity and (b) conductivity of the target and the actual ones.

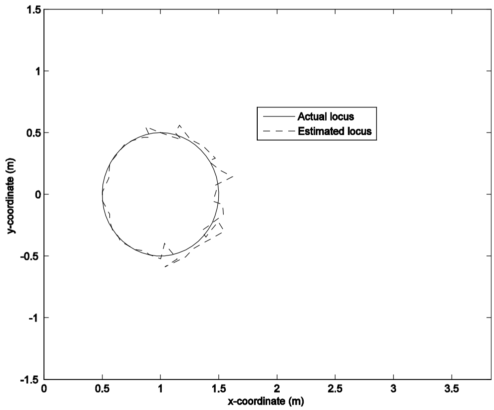

Figure 4. Actual track versus the estimated one.

Table 1. Error analysis for dielectric properties and tacking positions.

	Average	**Minimum**	**Maximum**
$\varsigma_{\varepsilon_r}$	0.0019	2.9215*e*–05	0.0055
ς_{σ}	0.1106	0.0027	0.4397
ς_{x_0}	0.0251	7.4937*e*–05	0.1159
ς_{y_0}	0.0370	6.5644*e*–05	0.2225

We use the relative errors of relative permittivity, conductivity, and position coordinate values

$$\varsigma_{\varepsilon_r} = \frac{|\varepsilon_{ract} - \varepsilon_{rpre}|}{\varepsilon_{ract}}, \quad \varsigma_{\sigma} = \frac{|\sigma_{act} - \sigma_{pre}|}{\sigma_{act}} \tag{9}$$

$$\varsigma_{x_0} = \frac{|x_{0act} - x_{0pre}|}{x_{0act}}, \quad \varsigma_{y_0} = \frac{|y_{0act} - y_{0pre}|}{y_{0act}} \tag{10}$$

to quantitatively evaluate the detection accuracy. Where the variables with subscript *act* are the actual values and those with subscript *pre* are the predicted ones. The minimum, maximum and average errors are listed in Table 1. From these statistical data, SVM for the detection of dielectric target in through-wall scenario demonstrates high fidelity.

5. CONCLUSION

A novel approach based on the SVM for dielectric target detection in through-wall problem is proposed. Good consistency between actual and estimated dielectric parameters makes this approach superior to other detection methods for through-wall dielectric target. Through-wall target tracking based on SVM is also discussed, and the results are acceptable with some small deviation from the true track. The SVM regression-based approach turns out to be effective for the detection of a single target, whereas they are not so suitable for the case of multiple targets. Since a classification approach can be used to detect multiple targets [20], a SVM classification-based technique for multiple targets detection in through-wall problem will be investigated. Background subtraction is employed to eliminate the reflection of the walls in this paper. However, this method can only compute the scattered field roughly. Besides, the method needs to know the information of the walls. So through-wall detection under unknown wall characteristics with SVM will be studied in the future work.

REFERENCES

1. Ferris, D. D. and N. C. Currie, "Survey of current technologies for through-the-wall surveillance (TWS)," *Proceedings of SPIE*, 1999.
2. Baranoski, E. J., "Through-wall imaging: Historical perspective and future directions," *Journal of the Franklin Institute-Engineering and Applied Mathematics*, Vol. 345, 556–569, 2008.
3. Ahmad, F., G. J. Frazer, S. A. Kassam, and M. G. Amin, "Design and implementation of near-field, wideband synthetic aperture beamformers," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 40, 206–220, 2004.
4. Ahmad, F., M. G. Amin, and S. A. Kassam, "Synthetic aperture beamformer for imaging through a dielectric wall," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 41, 271–283, 2005.
5. Wang, G. Y. and M. G. Amin, "Imaging through unknown walls using different standoff distances," *IEEE Transactions on Signal Processing*, Vol. 54, 4015–4025, 2006.
6. Ahmad, F., M. G. Amin, and G. Mandapati, "Autofocusing of through-the-wall radar imagery under unknown wall characteristics," *IEEE Transactions on Image Processing*, Vol. 16, 1785–1795, 2007.
7. Soldovieri, F. and R. Solimene, "Through-wall imaging via a linear inverse scattering algorithm," *IEEE Geoscience and Remote Sensing Letters*, Vol. 4, 513–517, 2007.
8. Song, L. P., C. Yu, and Q. H. Liu, "Through-wall imaging (TWI) by radar: 2-D tomographic results and analyses," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 43, 2793–2798, 2005.
9. Dehmollaian, M. and K. Sarabandi, "Refocusing through building

walls using synthetic aperture radar," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 46, 1589–1599, 2008.

10. Li, L. L., W. J. Zhang, and F. Li, "A novel autofocusing approach for real-time through-wall imaging under unknown wall characteristics," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 48, 423–431, 2010.
11. Zhang, W., A. Hoorfar, and L. Li, "Through-the-wall target localization with time reversal music method," *Progress In Electromagnetics Research*, Vol. 106, 75–89, 2010.
12. Bermani, E., A. Boni, S. Caorsi, and A. Massa, "An innovative real-time technique for buried object detection," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 41, 927–931, 2003.
13. Bermani, E., A. Boni, S. Caorsi, M. Donelli, and A. Massa, "A multi-source strategy based on a learning-by-examples technique for buried object detection," *Progress In Electromagnetics Research*, Vol. 48, 185–200, 2004.
14. Bermani, E., A. Boni, A. Kerhet, and A. Massa, "Kernels evaluation of SVM-based estimators for inverse scattering problems," *Progress In Electromagnetics Research*, Vol. 53, 167–188, 2005.
15. Zhang, Q. H., B. X. Xiao, and G. Q. Zhu, "Inverse scattering by dielectric circular cylinder using support vector machine approach," *Microwave and Optical Technology Letters*, Vol. 49, 372–375, 2007.
16. Vapnik, V. N., *The Nature of Statistical Learning Theory*, Springer Verlag, 2000.
17. Smola, A. J. and B. Scholkopf, "A tutorial on support vector regression," *Statistics and Computing*, Vol. 14, 199–222, 2004.
18. Kim, Y. and H. Ling, "Through-wall human tracking with multiple Doppler sensors using an artificial neural network," *IEEE Transactions on Antennas and Propagation*, Vol. 57, 2116–2122, 2009.
19. Du, K. L., M. N. S. Swamy, and I. Ebrary, *Neural Networks in a Softcomputing Framework*, Springer, 2006.
20. Massa, A., A. Boni, and M. Donelli, "A classification approach based on SVM for electromagnetic subsurface sensing," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 43, 2084–2093, 2005.