Estimating distributed objects inside buildings by moving sensors

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Abstract: We develop a radar system with a moving sensor scheme for localizing distributed objects hidden inside buildings. We first estimate the unknown building wall parameters, using geometrical optics (ray tracing) model and maximum likelihood approach. Time-of-arrival information is evaluated at different locations and utilized to estimate the position and shape of the object. We consider the influence of the wall on the signal propagation. Simulations results in the 2D case verify the accuracy of the proposed method.

Keywords: through-the-wall, radar imaging, time-of-arrival, range-gate, wideband signals.

1. Introduction

In this paper, we address an important problem in urban warfare - that is peering inside buildings using electromagnetic sensing. This is a difficult task due to complex and usually unknown environment. Recent publications on this topic focus on simplified scenarios, such as estimating locations of point scatterers behind a single wall with unknown parameters [1-2]. In realistic situations, the point-scatterer approximation may not be valid since objects are close to the sensing system.

We propose a radar technique for detecting distributed objects hidden behind walls and other opaque obstacles. We use moving sensors to form a virtual array and increase spatial resolution. We tackle some problems that may be encountered in practical realizations, such as unknown wall parameters. In contrast to [1-2], we use parametric (physical) models to determine the permittivity and thickness of the wall.

The proposed technique is simulated using a 2D electromagnetic model, which is described in Section 2. One possibility to distinguish among various reflections, to remove the clutter, and to determine the distance between the antenna and the target is to employ range-gating [3], as presented in Section 3. Finally, in Section 4, we present some results of the simulations.

2. Electromagnetic modeling

In our modeling, we use a 2D method of moments (MoM) code, since electromagnetic modeling of electrically large 3D structures (such as buildings with occupants) is still inadmissibly time-consuming. However, the approach we propose for estimating positions of hidden objects is general and can be easily applied to 3D problems.

We have developed the MoM code by generalizing the program from [4] to include arbitrarily shaped lossy-dielectric objects. The program uses the equivalence principle to divide the system under consideration into a number of subsystems (entities), each of them being filled with a homogeneous medium.

In our case, the system consists of probes (conductors whose cross section is electrically small), lossy-dielectric walls of the building, and an object inside the building (identification target). The program excites one probe at a time by an impressed electric field, calculates equivalent electric and magnetic currents on the surfaces of all entities, and finally evaluates the net electric currents in all probes. The result is a matrix relation of the form

$$\begin{bmatrix} I_1 \\ \vdots \\ I_M \end{bmatrix} = \begin{bmatrix} y_{11} & \dots & y_{1M} \\ \vdots & & \vdots \\ y_{M1} & \dots & y_{MM} \end{bmatrix} \begin{bmatrix} E_1 \\ \vdots \\ E_M \end{bmatrix}, \quad (1)$$

where M is the number of probes.

Increasing the number of probes can increase the performance of the radar. However, the number of probes is technically limited in real systems. One way to resolve this problem is to use moving sensors [5-6]. We assume that one moving sensor consists of several probes. Measurements obtained from multiple locations increase spatial resolution and enable object shape estimation and classification.

Accurate modeling necessitates independent simulations for each position of the sensor. However, this is computationally costly even in the 2D scenario. Instead, we consider the case where several static sensors are simultaneously present, so that each sensor location corresponds to one position of the moving sensor. In general, such a model introduces an error due to coupling among the static sensors. Nevertheless, if probes are thin and if the impedance (z) parameters are used instead of the admittance (y) parameters, the modeling error is negligibly small.

An element of the impedance matrix, z_{ij}, is defined as the ratio of the induced electric field in probe #j and the current in probe #i, when net currents in all other probes (conductors) are zero. Since a thin probe with zero net current has negligible influence on the field distribution in other conductors, the relevant impedance coefficients remain practically the same whether they are calculated for a group of probes treated one at a time, or for all probes analyzed simultaneously. This is not the case for y parameters because currents are induced in all conductors when one conductor is excited. To that purpose, we determine impedance coefficients by inverting the admittance submatrix (1),

$$\begin{bmatrix} E_1 \\ \vdots \\ E_M \end{bmatrix} = \begin{bmatrix} z_{11} & \dots & z_{1M} \\ \vdots & & \vdots \\ z_{M1} & \dots & z_{MM} \end{bmatrix} \begin{bmatrix} I_1 \\ \vdots \\ I_M \end{bmatrix}. \quad (2)$$

We perform the analysis over a wide band of frequencies. The time-domain waveforms are reconstructed using the inverse Fourier transform.

3. Signal processing

We are primarily interested in the target object located inside the building. Hence the parameters of the wall can be considered as nuisance parameters. However, to estimate accurately the position of the object, we need to assess also the wall width and its electrical properties. We model each wall as a homogeneous lossless dielectric slab of a constant thickness.

We reduce complexity of the problem by dividing it in two simpler tasks: (i) estimation of the wall parameters, and (ii) estimation of the object location and shape using the known wall parameters. To that purpose, we apply range-gating. We limit the first range gate to specular reflections from the front and back side of the nearest wall, since they contain most of information about the wall characteristics. Reflections from the object are captured in the second range-gate, as we illustrate in Fig. 1.

In this paper, we consider a portable two-probe system where one probe transmits radar pulses, while both probes receive reflected signals. However, results are easily generalized to more complex systems. For the measurement model in probe #i, $i=1,2$, we use the following equation,

$$Y_i(n)=E_i(n;\varepsilon_r,w)+W_i(n),\quad n=1,\ldots,N\,, \tag{3}$$

where $Y_i(n)$, is the sample of the measured electrical field in the frequency domain, $E_i(n)$ is the transmitted signal, $W_j(n)$ is the measurement noise, N is the number of frequencies, ε_r the permittivity of the wall, and w the wall thickness. We assume zero-mean, white Gaussian noise that is uncorrelated with the signal. We apply the inverse Fourier transform on (3) to obtain the time-domain relationship

$$y_i(k)=e_i(k;\varepsilon_r,w)+w_i(k),\quad k=1,\ldots,N\,. \tag{4}$$

Due to the properties of Fourier transform, noise samples $w_i(k)$, are also zero-mean, independent Gaussian random variables. Walls are electrically large structures, hence the transmitted signal in the first range-gate, $e_i(k)$, is efficiently modeled by ray tracing [7]. We use the maximum likelihood approach to estimate the wall parameters,

$$[\hat{\varepsilon}_r,\hat{w}]=\arg\min_{\varepsilon_r,w}\sum_{k=1}^{N}\left(y_i(k)-e_i(k;\varepsilon_r,w)\right)^2\,. \tag{5}$$

We may take the advantage of prior knowledge about the building to set up initial guesses and speed up the search.

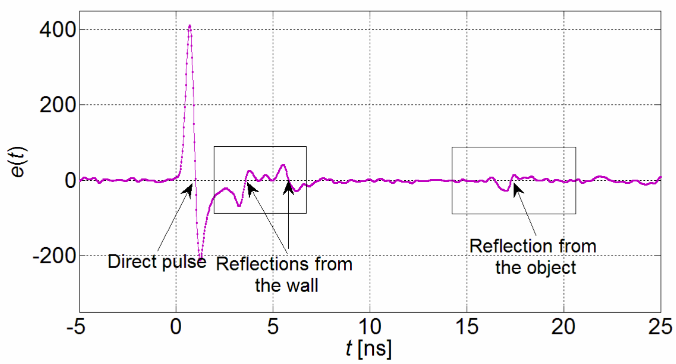


Fig. 1. Electric field induced in the probe and appropriate range-gates.

If we repeat the estimation for different sensor locations, we can detect variations in wall parameters along the sensor path, and hence improve the accuracy of object positioning.

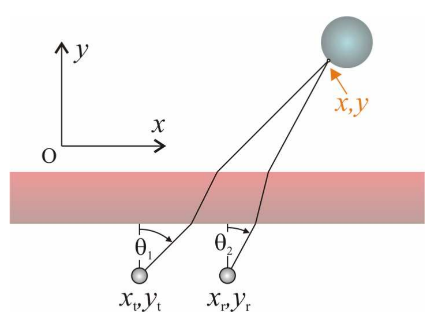


Fig. 2. Two-probe system and adopted coordinate system.

Once the wall parameters have been estimated, we move to the second range-gate and estimate the location of the object. To that purpose, we use the time-of-arrival (ToA) information obtained at different locations. We assume measurements are taken at known sites.

We use a matched filter to determine times-of-arrival of reflected signals and consider only reflections with a high correlation coefficient (more than 0.9) to eliminate diffraction from wall edges (building corners). Times-of-arrival are used to form constant-range contours with intersection points on the surface of the object. In our calculations, we assume that the distance between the probes is small compared to the distance to the object, so that both antennas receive signals reflected from approximately the same point on the body contour. For the sake of clarity, we will write equations for the case of one wall. We adopt a coordinate system as shown in Fig. 2 .

Constant- range curves seen from the first and second probe, respectively, are:

$$x = x_t + c\tau_1 \sin\theta_1 / 2 + w\frac{\sin\theta_1}{\sqrt{\varepsilon_r - \sin^2\theta_1}}(1-\varepsilon_r)\ ,\ \ y = y_t + c\tau_1\cos\theta_1/2 + w\left(1 - \frac{\varepsilon_r\cos\theta_1}{\sqrt{\varepsilon_r - \sin^2\theta_1}}\right), \quad (6)$$

$$x = x_r + c(\tau_2 - \tau_1/2)\sin\theta_2 + w\frac{\sin\theta_2}{\sqrt{\varepsilon_r - \sin^2\theta_2}}(1-\varepsilon_r),\ \ y = y_r + c(\tau_2 - \tau_1/2)\cos\theta_2 + w\left(1 - \frac{\varepsilon_r\cos\theta_2}{\sqrt{\varepsilon_r - \sin^2\theta_2}}\right), \quad (7)$$

where τ_1 and τ_2 are times-of-arrival at the first and second probe, respectively. The meeting point of these curves defines one point on the object surface. When the sensor moves around the building, the signal is reflected from different points on the object. In this way, an image of the object is created that can be used for object classification.

4. Simulations

We simulate the scenario where moving sensor consisting of two probes takes the measurements around the building, as depicted in Fig. 5. The sensor transmits a wideband Gaussian pulse. The pulse is synthesized in the frequency domain, where frequency is swept from 10 MHz to 2.5 GHz in 10 MHz steps. This frequency range is selected being the optimal choice for the through-the-wall target identification.

Firstly, we estimate the wall parameters, where the adopted values for the dielectric permittivity and wall width are $\varepsilon_{r0} = 3$ and $w_0 = 0.2$, respectively. The estimation is performed for SNR =10 dB, and SNR = 20 dB, where the signal-to-noise ratio is calculated with respect to the power of the useful signal (i.e., the power of the signal that passed back through the wall). Maximum likelihood estimator converged to the true values in both cases. Note that the minimization function (5) depends mostly on the effective thickness of the wall, $w_e = w\sqrt{\varepsilon_r}$, rather than the permittivity and the width alone, as illustrated in Fig. 3. However, this is not a serious problem, since the times-of-arrival (and hence the object localization) are primarily influenced by the effective thickness of the wall as well.

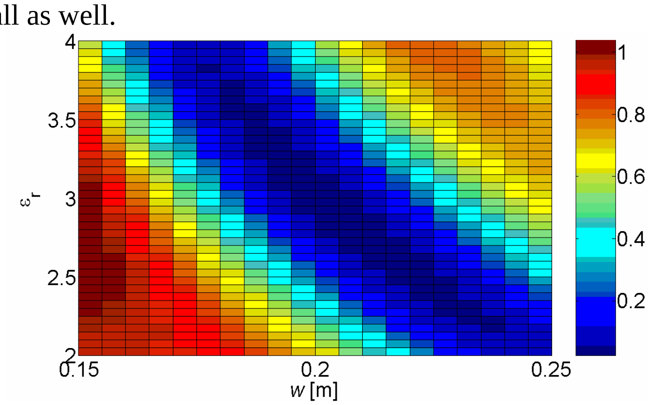


Fig. 3. Minimization function for MLE estimator, normalized with respect to the power of received signal as a function of wall parameters.

We calculate the mean-square-error for the effective thickness of the wall to evaluate the performance of maximum likelihood estimator. MLE is asymptotically unbiased and asymptotically attains Cramer-Rao Lower Bound. Asymptotical mean-square-error is found as a square root of CRB and shown in Fig. 4.

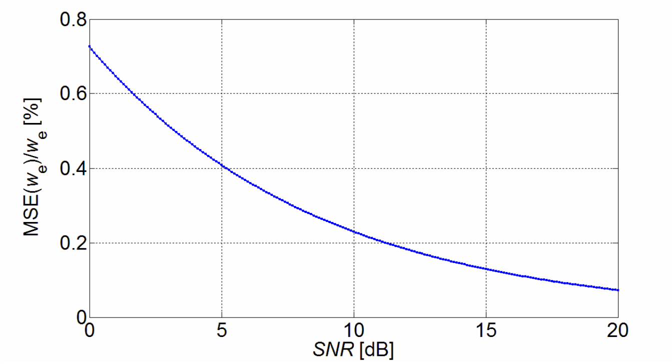
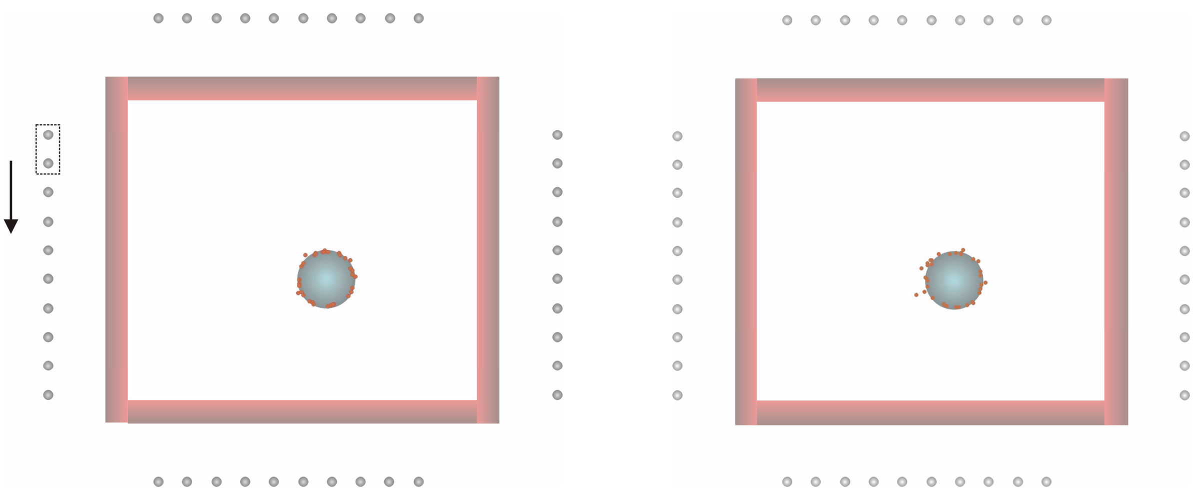


Fig. 4. Asymptotical mean-square-error for the effective thickness of the wall as a function of signal-to-noise ratio.

Finally, we estimate the location of the object, which is a perfectly conducting infinitely long circular cylinder of radius a = 0.2 m. Estimated points on the object, obtained for *SNR* =10 dB and *SNR* = 20 dB, are shown in Fig. 5.



(a) (b)

Fig. 5. Positions of the moving sensor and estimated contour of the object of unknown shape and location, hidden behind walls of unknown permittivity and width, for (a) *SNR* = 20 dB and (b) *SNR* = 10 dB.

5. Conclusions

We developed a moving wide-band radar sensor system for localizing distributed objects hidden behind walls. Using range-gating, we treated separately the estimation of the wall parameters and object position. Data obtained at different sensor locations were utilized to estimate the shape of the object. The estimation was based on efficient physical models that take into account the signal propagation through the wall. Simulation results confirmed the accuracy and applicability of the proposed system.

References

[1] G. Wang, and M. Amin, "Imaging Through Unknown Walls Using Different Standoff Distances," *IEEE Trans. on Signal Processing*, Vol. 54, No. 10, pp. 4015-4025, October 2006.
[2] F. Ahmad, M. G. Amin, S. A. Kassam, “Synthetic Aperture Beamformer for imaging through a dielectric wall”, *IEEE Trans. on Aerospace and Electronic Systems*, Vol. 41, No. 1, pp. 271-283, January 2005.
[3] M. I. Skolnik, *Radar handbook*, 2nd edition, McGraw-Hill 1990.
[4] Djordjević, A.R., Sarkar, T.K., Rao, S.M., "Analysis of finite conductivity cylindrical conductors excited by axially-independent TM electromagnetic field", *IEEE Trans. Microwave Theory Techn.*, Vol. MTT-33, No. 10, pp. 960-966, Oct. 1985.
[5] D. G. Falconer, R. W. Ficklin, K. G. Konolige, “Robot-Mounted Through-Wall Radar for Detecting, Locating, and Identifying Building Occupants”, *Proceedings of IEEE International Conference on Robotics and Automation*, San Francisco, April 2000.
[6] B. Porat, and A. Nehorai. “Localizing vapor-emitting sources by moving sensors,” *IEEE Trans. Signal Processing*, vol. 44, no. 2, pp.1018-1021, Apr. 1996.
[7] E. A. Glassner, *An Introduction to Ray Tracing*. San Diego, CA: Academic, 1989.