EQUIPMENT AND PROCEDURES FOR MICROWAVE NONDESTRUCTIVE EVALUATION OF LAPIDEOUS MATERIALS

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ABSTRACT

A procedure for in-field nondestructive evaluation of lapideous materials is described. A portable instrument has been developed to evaluate the average permittivity of the probed volume. This is based on measuring the resonance frequency of a microstrip patch sensor. Once this hardware is enabled to perform coherent measurements, the optimization of an edge-preserving energy functional can yield high-resolution permittivity range profiles.

1 INTRODUCTION

Portability, user-friendliness and unexpensiveness are among the most important requirements of any nondestructive evaluation system to be used outside a laboratory by non-specialist personnel. These requirements hold true for both the probing-measurement hardware and any possible online imaging-display software. In particular, these issues are relevant in characterizing lapideous materials, with applications, e.g., in diagnostics of architectural elements or online quality control of building materials. A complete dielectric characterization of an object should be a 3D map of its complex permittivity. Although microwaves are sensitive to permittivity, to the state of the art, this would require complicated scanning systems and expensive software procedures (see [1] for a collection of papers also dealing with experimental issues). For this reason, we split the problem in different subtasks, whose outputs carry useful pieces of information for practical nondestructive diagnosis. In particular, we are able to build 2D maps of volume-averaged permittivities by only measuring the resonance frequencies of suitable structures loaded by the material under test. To this purpose, we developed a dedicated microwave sensor and a simplified scalar network analyzer by which we can probe lapideous materials, typically with permittivities in the range 4-12 and possible inclusions of air or other etherogeneous materials. An inhomogeneity in one of these 2D maps reveals an anomaly in the mean permittivity, but does not give any other information on the physical-geometrical features of the object. A modification in our hardware can enable us to measure the complex reflection coefficients within a certain band, instead of the resonance frequency. From such data sets, by applying a specific genetic algorithm, we can reconstruct high-resolution permittivity range profiles. Besides being able to treat high-contrast objects, our algorithm assures a fairly accurate location of the interfaces between strongly etherogeneous material layers.

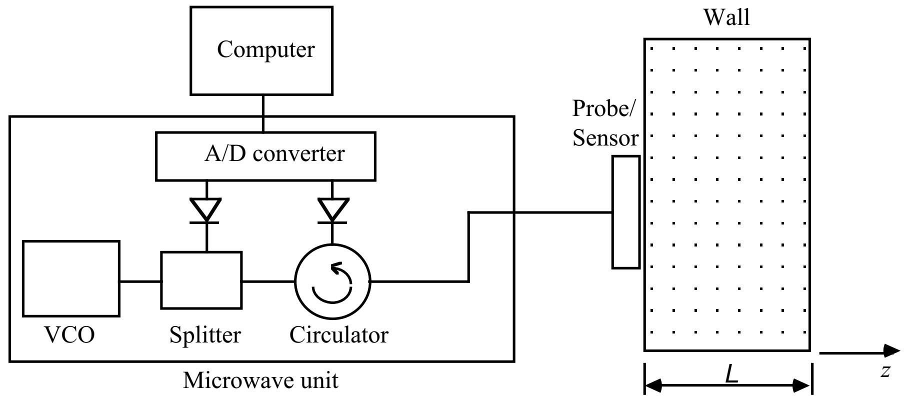

Fig. 1: *Monostatic measurement setup*

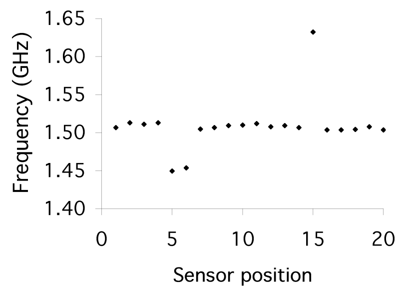

Fig. 2: *Resonance frequency measurements on an inhomogeneous concrete block*

2 A PORTABLE SENSOR FOR VOLUME DIELECTRIC CHARACTERIZATION

Let us suppose we have a lossless dielectric wall probed as shown in Figure 1. The voltage-controlled oscillator produces a swept-frequency signal, which is split to obtain a reference signal and a test signal sent to the probe/sensor through a circulator. The circulator also separates the test signal and the signal reflected by the sensor. The reference and the reflected signals are then sent to a pair of crystal detectors and digitized. A software procedure evaluates the resonant frequency as the minimizer of the reflection coefficient. The sensor is a microstrip square patch with air substrate, with resonance frequency determined by the patch size, the substrate permittivity and, when loaded by the material under test, by the mean permittivity ε_{mat} of the probed volume. In formulas, we have [2]:

$$f = \frac{A}{\sqrt{\varepsilon_{eff}}} \qquad (1)$$

$$\varepsilon_{eff} = \frac{1+\varepsilon_{mat}}{2} + \frac{1-\varepsilon_{mat}}{2}\left[1+12t/W\right]^{-1/2} \qquad (2)$$

where f is the resonance frequency, A is a constant, t is the substrate thickness, W is the patch size, and it has been considered that the microstrip substrate is air. The resonance frequencies measured by scanning the surface of a 26×26×14 cm^3 concrete block on a regular grid are reported in Figure 2. Apparently, the resonance frequency is quite sensitive to the typical inhomogeneities found in concrete. If the material is thick enough to be considered infinite in

z direction, (1) and (2) can be used to evaluate ε_{mat}. If the material is a two-phase mixture [3], the volume percentages of the mixture components can be obtained. For example, air content (porosity) can be evaluated after suitable calibration. If the material is not so thick, the resonance frequency can be used to estimate thickness. Absolute measurements can be obtained by calibration with known samples.

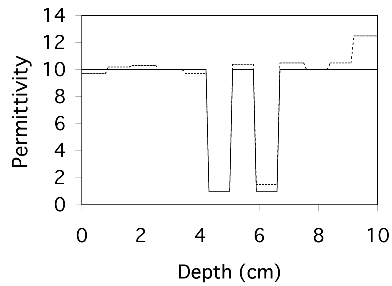

Fig. 3: *Simulated concrete wall with relative permittivity 10, with two air inclusions 0.833 cm apart. Number of layers assumed: 12. Simulated noisy data with 25 dB SNR. Solid line: original permittivity profile. Dotted line: reconstructed profile.*

3 RECONSTRUCTING THE RANGE PROFILE

Let us assume now that the wall in Figure 1 has a permittivity that only depends on the z coordinate, and is composed of a finite number M of homogeneous layers. If coherent reflection measurements are available for N frequencies within the working range, nonlinear inverse scattering procedures can be applied to evaluate a permittivity range profile at each sensor location. The measurement system can be modified accordingly: as an example, the crystal detectors could be replaced by a phase-quadrature detector. Our reconstruction algorithm estimates the range profile by minimizing the functional [4]:

$$F(\varepsilon) = d^2(\Gamma_{meas} - \Gamma_{est}) + \lambda \sum_{m=1}^{M-1} (\varepsilon_{m+1} - \varepsilon_m)^2 (1 - l_m) + \alpha l_m \qquad (3)$$

which contains a data fit term and an edge-preserving regularization term [5]. In (3), ε is a real M-vector, whose elements are the mean permittivities of the different layers, Γ_{meas} is the complex measurement N-vector, Γ_{est} is the measurement vector evaluated numerically from the current permittivity profile, and d is a distance that gives a data fit measure. A good data fit alone, however, does not guarantee e stable solution, since the problem is heavily ill posed. The summation over m is an edge-preserving stabilizer, which forces a locally smooth solution. It penalizes large discontinuities between adjacent layers where the binary variables l_m (line elements) are equal to zero. Conversely, if a sensible discontinuity is likely to occur between layers m and $m+1$, l_m assumes value 1 thus breaking the smoothness constraint. The number of discontinuities introduced is controlled by the terms $\alpha\, l_m$. The *regularization parameter*, λ, establishes a compromise between data fit and smoothness. We minimize this functional by a genetic algorithm, characterized by uniform crossover, simple elitism and adaptive mutation probability [4,6]. From simulated experiments, we have found that high contrast values can be reconstructed, and the discontinuities can be located very accurately, thus providing a good spatial resolution. A representative example of our results is shown in

Figure 3. Two air inclusions located 0.833 cm from each other in a 10 cm-thick wall with permittivity 10 can be clearly distinguished. Of course, the resolution achievable is a function of the SNR. We are now about to complete the simulations in order to evaluate the performance of the technique in the cases of our interest. After assessing the method with real experimental data obtained by general-purpose laboratory equipment, we will move to the problem of extending our dedicated hardware. The computational cost of the reconstruction algorithm is a major inconvenience. The 2D maps of Section 2, however, can also be obtained readily from coherent measurements. Range profiles can then be reconstructed offline for the areas where significant inhomogeneities are detected. If quasi-real-time performance will be obtained, a high-resolution online analysis will also be feasible.

4 CONCLUSIONS

We described a step-by-step approach to build a portable system for in-field nondestructive diagnosis applications. The simple dedicated system we already developed is able to provide the volume-averaged permittivities of the material. The data acquisition, processing and display in this case can be made in quasi-real time. This is not the case, at present, with our range profile reconstruction procedure. Even in this case, however, the data acquisition is very fast, and the same data can be used to evaluate the mean permittivity map. Thus, the equipment can be used for both an immediate diagnosis and an offline reconstruction of high-resolution profiles. The system can be used for either absolute or relative measurements. For example, in quality control applications, the mean permittivity can be obtained by comparison with a set of reference samples. A problem that is still to be addressed is the application of this technique to sensibly lossy materials.

ACKNOWLEDGEMENT

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