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Numerical Validation and Experimental Results of a Multi-Resolution SVM-Based Classification Procedure for Breast Imaging

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Introduction

X-Ray mammography is the principal technique for breast cancer screening in clinical practice. However, X-ray mammography presents different drawbacks showing that alternative technologies are desirable. For example, the difficulty in detecting the breast tumors at the earlier stage, the destructive effects of the ionizing X-rays on the irradiated tissues, low efficiency in dense breasts and with cancer near the chest wall. Other minor but still negative aspects are also the discomfort due to the breast compression and the expensive costs [1].

Since the conductivity and permittivity of the breast tumors differ significantly from healthy breast tissues, microwave imaging techniques are promising alternatives to standard clinical practice. They are widely considered cost effective and above all non-invasive since they illuminate the breast with very low-power and non-ionizing microwave signal [2]. Starting from the scattered microwave signal the problem of detecting the cancer and estimating its position represents an inverse scattering problem that needs to be solved iteratively when some traditional deterministic techniques are applied. Most of them have performances strictly dependent from the initialization of the trial solution [3]. Stochastic methods, such as Particle Swarm Optimizer (PSO) or Genetic Algorithm (GA) overcome this drawback by solving the detection problem as a global optimization problem [4]. However, even if they have the capabilities to find the global minimum of a given functional, the computational load still remain very high.

Recent progress in machine learning has promoted to solve medical problems by means of Learning by Example (LBE) algorithms, for example by assisting radiologists in image analysis with diagnostic classification mechanisms [5].

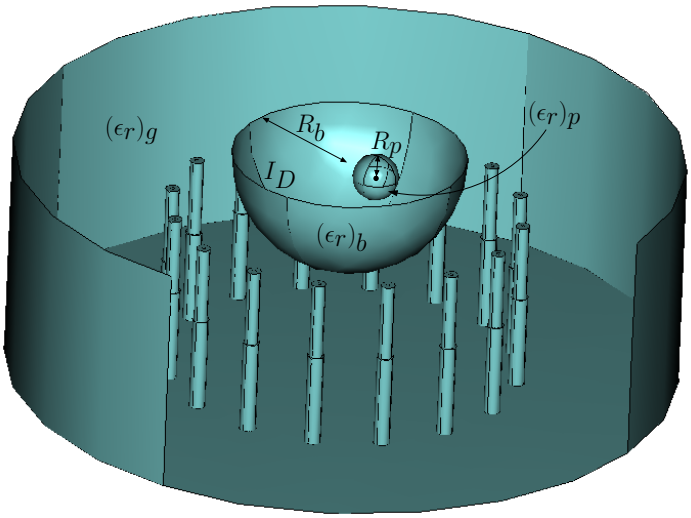

Fig. 1 - Three-dimensional geometry of the synthetic imaging system

These kinds of approaches reduce high computational costs to fit real-time requirements in practical applications. In this paper, the inversion process is recast as a classification process by integrating a SVM-based classifier with an iterative multi-zooming procedure (IMSA) for early detection of breast cancer.
Once the training procedure of the system is completed, the detection of the pathology is real-time estimated by generating a multi-resolution risk-map of malignant tissue presence. The spatial resolution of the probability risk-map is iteratively enhanced at each step of the IMSA methodology only in the Regions of Interest (ROIs) where the pathology is supposed to be located. The effectiveness of the approach has been numerically validated considering some test cases reproducing the geometry and the characteristics of a prototypal imaging system used to evaluate the applicability of the proposed methodology also when applied to experimental measurements.

Mathematical Formulation

Let us consider the three-dimensional model shown in fig. 1. The hemisphere of radius R_b represents the simplified breast model as well as the investigation domain I_D where the pathology of radius R_p and center $B_p = \left(x_p, y_p, z_p\right)$ can reside. The imaging system used both for numerical validation and experimental measurements, consists of a circular array of S dipoles installed into a cylindrical tank filled with a coupling liquid that maximizes the coupled microwave energy [6]. Each dipole acts sequentially as transmitter while the remaining $S-1$ dipoles measure the total electric field all round I_D. As the procedure is completed, the multi-view system collects $S \times (S-1)$ field samples. From the knowledge of the measured data, the arising problem is that of

determining the presence and the position of the pathology by generating a probability risk-map of I_D. Towards this end, the problem can be solved by a SVM-based classification approach [7] able to classify whatever input pattern after an offline training phase. The training of the SVM requires the knowledge of T different samples constituting the so-called training set $\mathbf{Y} = \{\mathbf{\Omega}, \pi_c, \sigma_c; c = 1,...,C\}_t \; t = 1,...,T$, being $\mathbf{\Omega}$ the t-th vector of data collected by the system and $\pi_c = (x_c, y_c, z_c), c = 1,...,C$ are randomly-chosen positions inside I_D where the respective class indexes $\sigma_c = [-1,1], c = 1,...,C$ are evaluated. More in detail, if $\delta < R_p$, δ being the distance between B_p and π_c, the state of the position π_c is $\sigma_c = 1$, otherwise it is set to $\sigma_c = -1$. Starting from these known relations among data, positions and classes, a suitable linear decision function $\Phi = \mathbf{w} \cdot \varphi(\mathbf{Y}) + b$ is determined in the higher dimensional feature space where the data are mapped through the nonlinear operator φ. The unknowns $\mathbf{w}, b$ are calculated during the training phase, according to the SVM methodology [8].

Once the decision function is generated, the successively acquired test data $\mathbf{\Omega}$ are processed by evaluating the a posteriori probability function $\Theta = \Pr\{\sigma_m = 1 | \mathbf{\Omega}\}, m = 1,...,M$, where M is the number of test positions. In order to achieve higher spatial resolution in the reconstructions, a multi-resolution representation of $\Theta_s, s = 1,...,S$ is obtained according to an iterative multi-resolution strategy [9]. At the first step $s = 0$ of the iterative process, a coarse risk-map of I_D is determined by means of the SVM classifier mapping the decision function Φ into the probability function Θ_1. Starting from the previously defined map, each step $s > 0$ is aimed at identifying the spatial regions of interest (*RoIs*) where the pathologies are supposed to be located and to improve the resolution only in those regions in order to enhance the accuracy of the reconstruction. The iterative procedure is stopped when the number and the dimension of the *RoIs* are stationary between two consecutive steps.

Numerical Model and Experimental Setup

In order to preliminary assess the capabilities of the proposed methodology, let us consider the three-dimensional model shown in Fig. 1 that numerically reproduces the geometry of the tomographic system developed to experimentally validate the SVM-based solution to the breast imaging problem. Figure 2 shows a preliminary version of the prototype. The model considers the $S = 16$ elements of the antenna array as monopolar probes circularly arranged around the breast and working at the frequency $F = 1.1GHz$. The cylindrical tank is filled with glycerin as coupling liquid whose relative dielectric constant is $(\varepsilon_r)_g = 23.43 - j18.48$. These characteristics reduce as much as possible the reflection of the microwave energy since they are close to the heterogeneously

dense breast tissue with constitutive parameter $(\varepsilon_r)_b = 17.72 - j15.41$. The hemisphere that models the breast has a radius $R_b = 0.187\lambda$, λ being the wavelength of the working frequency F, and the inclusion that is a sphere of radius $R_p = 0.036\lambda$, has malignant tissue characteristics $(\varepsilon_r)_p = 53.46 - j18.26$. The training set $\mathbf{Y}$ has been generated by considering $T = 200$ different configurations of the breast model. More in detail, for each training example the position as well as the size of the pathology randomly changes in order to enhance the generalization capabilities of the SVM. The data acquired in presence of a healthy breast has been also included in the training set.

References

[1] Q. H. Liu, Z. Q. Zhang, T. T. Wang, J. A. Brgan, G. A. Ybarra, L. W. Nolte, and W. T. Joines, "Active microwave imaging I - 2-D forward and inverse scattering methods," *IEEE Trans. Microwave Theory Tech.*, vol. 50, no. 1, pp. 123–133, Jan. 2002.

[2] P. M. Meaney, M. W. Fanning, D. Li, S. Poplack, and K. D. Paulsen, "A clinical prototype for active microwave imaging of the breast," *IEEE Trans. Microw. Theory Tech.*, vol. 48, no. 11, pp. 1841–1853, Nov. 2000.

[3] A. E. Souvorov, A. E. Bulyshev, S. Y. Semenov, R. H. Svenson, A. G. Nazarov, Y. E. Sizov, and G. P. Tatsis, "Microwave tomography: A two-dimensional newton iterative scheme," *IEEE Trans. Microw. Theory Tech.*, vol. 46, pp. 1654–1659, Nov. 1998.

[4] S. Caorsi, A. Massa, M. Pastorino, and A. Rosani, "Microwave medical imaging: Potentialities and limitations of a stochastic optimization technique," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 8, pp. 1909–1916, Aug. 2004.

[5] R. Lucht, S. Delorme, and G. Brix, "Neural network-based segmentation of dynamic MR mammographic images," *Magn. Reson. Imag.*, vol. 20, pp. 147–154, 2002.

[6] P. Meaney, S. Pendergrass, M. Fanning, D. Li, and K. Paulsen, "Importance of using a reduced contrast coupling medium in 2D microwave breast imaging," *J. Electromagn. Waves Applicat.*, vol. 17, no. 2, pp. 333–355, 2003.

[7] A. Massa, A. Boni, and M. Donelli, "A classification approach based on SVM for electromagnetic subsurface sensing," *IEEE Trans. Geosci. Remote Sens*, vol. 43, no. 9, Sept. 2005.

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

[9] S. Caorsi, M. Donelli, D. Franceschini, and A. Massa, "A new methodology based on an iterative multiscaling for microwave imaging," *IEEE Trans. Microw. Theory Tech.*, vol. 51, no. 4, pp. 1162-1173, Apr. 2003.