Artificial Neural Networks for Quantitative Microwave Breast Imaging

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Keywords: Microwave Imaging, Inverse Scattering, Artificial Neural Network, MIMO Systems, Biomedical Imaging.

Abstract: This paper is focused on the use of artificial neural networks (ANNs) for biomedical microwave imaging of breast tissues in the framework of advanced breast cancer imaging techniques. The proposed scheme processes the scattered field collected at receivers locations of a multiview-multistatic system and aims at providing an estimate of the morphological and dielectric features of the breast tissues, which represents a strongly non-linear scenario with several challenging aspects. In order to train the network, a simulated data set has been created by implementing the forward problem and an automatic randomly-shaped breast profile generator based on the statistical distribution of complex permittivity of breast biological tissues was developed. Some numerical tests were carried out to evaluate the performance of the proposed method and, in conclusion, we found that the use of ANNs for quantitative biomedical imaging purposes seems to be very promising.

1 INTRODUCTION

Inverse scattering (IS) techniques represent a valuable imaging modality for several applications in which a non-destructive testing is required (Massa et al., 2005; Persico et al., 2018; Ambrosanio and Pascazio, 2015), especially for biomedical diagnostics (Bevacqua et al., 2019; Ambrosanio et al., 2016). The capability of these approaches to retrieve physical as well as geometrical properties of the objects under test located in an inaccessible domain by exploiting electromagnetic waves makes them very attractive.

In order to detect inhomogeneities in a medium, the scattered field related to these targets is collected and processed in a coherent fashion. Nevertheless, the intrinsic ill-posedness and strong non-linearity of the inverse problem at hand still represent a big issue (Colton and Kress, 2012; Isernia et al., 1997). Classical approaches exploit some linear and nonlinear approximations to handle the non-linearity issue, such as the iterative Born method, the distorted Born iterative method (Ahsan et al., 2018) and others (Bevacqua and Isernia, 2018; Estatico et al., 2016). Therefore, by minimising a proper functional, the mismatch between estimated and measured data is evaluated at each step of the iterative procedure in order to provide a recovery of the unknown object.

Unfortunately, these approaches are time-consuming and computationally expensive, and thus not suitable for real-time applications. However, some non-iterative methods are available to provide reconstructed images in a fast fashion, but they are still not accurate in the recoveries, especially if strong scatterers are present in the region of interest.

In this framework, some recent methodologies based on artificial neural networks (ANNs) and more in general on machine learning may be very beneficial to face the drawbacks related to classical approaches (Lucas et al., 2018). Recently, machine learning has attracted attention with interesting results for image classification and segmentation, but ANNs have proven to provide good results also in case of ill-posed inverse problems (Caorsi and Gamba, 1999).

In this paper, we propose an approach based on neural networks for the quantitative biomedical imaging of breast profiles via a direct inversion scheme. Thus, the output of the network consists in an estimate of the complex permittivity profile given the scattered field as input.

2 MATHEMATICAL BACKGROUND

For the sake of simplicity, a bounded and simply-connected investigation domain Ω is considered in

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Ambrosanio, M., Franceschini, S., Baselice, F. and Pascazio, V.
Artificial Neural Networks for Quantitative Microwave Breast Imaging.
DOI: 10.5220/0009172802040208
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 2: BIOIMAGING*, pages 204-208
ISBN: 978-989-758-398-8; ISSN: 2184-4305

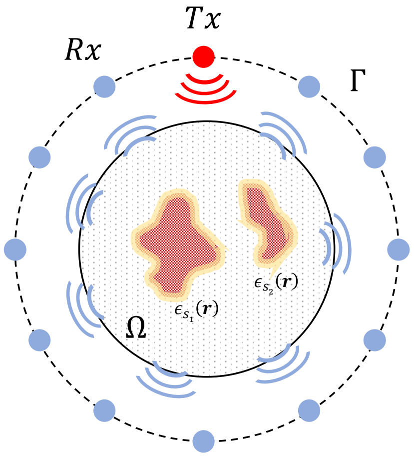

Figure 1: Sketch of the multiview-multistatic imaging system for the non-invasive testing of the imaging domain Ω. The antennas are locate on a measurement curve Γ.

a homogeneous background medium whose electromagnetic features $(\varepsilon_b, \sigma_b)$ or an estimate of theirs are assumed to be known a priori. All the scatterers, as well as the background medium, are assumed to have a constant magnetic permeability equal to $\mu_0 = 4\pi \cdot 10^{-7}$ H/m.

In the considered scattering experiments, an impinging time-harmonic wave illuminates the objects of interest at a certain frequency by a transmitting antenna, and the corresponding scattered field generated by the interaction of the incident field with the targets is collected by some receivers located on a measuring curve which surrounds the imaging domain. In order to simplify the mathematical formulation, a scalar two-dimensional (2D) scenario will be considered in the following.

The incident fields are modelled as transverse-magnetic (TM) polarised with respect to z axis which represents the symmetry direction and all the scatterers located in the domain Ω are assumed to have a constant section along this axis, as shown in Fig. 1. Under these hypotheses and by omitting the time factor $e^{j\omega t}$, the scattering problem can be stated as a 2D scalar equation, known as electric field integral equation (EFIE), i.e. (Colton and Kress, 2012):

$$\begin{aligned} &E_s(\boldsymbol{r}_R, \boldsymbol{r}_T, \omega) = \\ &= k_b^2 \int_\Omega G(\boldsymbol{r}_R - \boldsymbol{r}', \omega)\chi(\boldsymbol{r}', \omega)E_t(\boldsymbol{r}', \boldsymbol{r}_T, \omega)d\boldsymbol{r}' = \\ &= \mathcal{A}_e[\chi E_t], \quad \boldsymbol{r}' \in \Omega, \quad \boldsymbol{r}_T, \boldsymbol{r}_R \in \Gamma, \end{aligned} \tag{1}$$

with:

$$\chi(\boldsymbol{r}, \omega) = \frac{\varepsilon_s(\boldsymbol{r}, \omega)}{\varepsilon_b(\omega)} - 1, \tag{2}$$

being the contrast function relating the electric properties of the objects inside the imaging domain ε_s to those of the homogeneous hosting medium ε_b at the working frequency ω, k_b is the wavenumber in the background medium, $\varepsilon_s(\boldsymbol{r}, \omega) = \varepsilon_s'(\boldsymbol{r}) - j\frac{\sigma_s(\boldsymbol{r})}{\omega\varepsilon_0}$ and $\varepsilon_b(\omega) = \varepsilon_b' - j\frac{\sigma_b}{\omega\varepsilon_0}$ are the complex permittivities of the targets and background medium, respectively. Finally, E_t, E_s are the total and scattered electric fields and $G(\boldsymbol{r}_R - \boldsymbol{r}', \omega)$ is the Green's function for the case of homogeneous background and observation points located along the measurement line. Under this assumption, the relationship between contrast and electric field becomes quite easy since it is a convolution; therefore, fast Fourier transform (FFT) codes can be adopted for its evaluation (Isernia et al., 1997).

The aforementioned problem, whose model is depicted in Eq. (1), aims at retrieving the unknown contrast function $\chi(\cdot)$ from the measurements of the scattered field collected at receivers locations and for different incident angles $E_s(\cdot)$. Thus, the proposed framework represents a multiple-input-multiple-output (MIMO) system, commonly referred to as multiview-multistatic. As most inverse problems, the attempt of retrieving the contrast function $\chi(\boldsymbol{r}, \omega)$, or equivalently the complex permittivity of the targets $\varepsilon_s(\boldsymbol{r}, \omega)$, from the measurement samples represents an ill-posed problem which needs proper regularisation strategies to obtain reliable solutions (Colton and Kress, 2012). Moreover, the problem at hand is also strongly nonlinear, and the degree of non-linearity (DNL) of the considered integral model depends on the electromagnetic and geometrical features of the targets embedded in the scattering region. Therefore, the higher the DNL, the harder the problem at hand and thus the difficulty of solving the inverse scattering problem as well as its computational burden.

In order to face these drawbacks and provide an efficient, almost real-time imaging strategy also in complicated, strongly non-linear scenarios, in the following a machine-learning-based approach is proposed.

3 ARTIFICIAL NEURAL NETWORK FOR QUANTITATIVE IMAGING

The reconstruction of the inner part of an unknown object from scattered field measurements is computationally expensive in both time and memory requirements. Thus, there is a strong interest in the development of online techniques for quantitative imaging purposes, whose reconstructions are obtained in a short time after the acquisition.

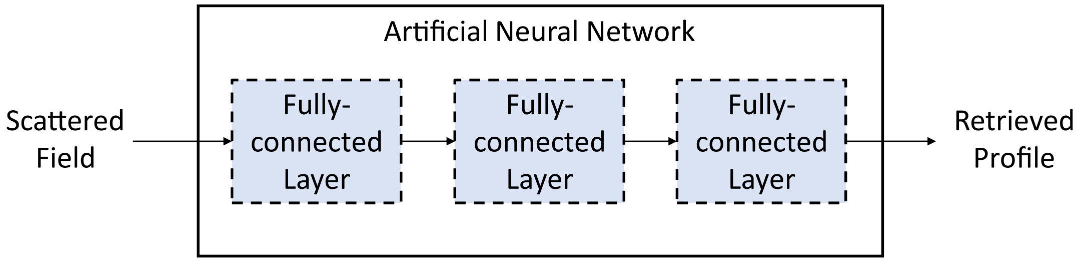

Figure 2: Architecture of the proposed network. This direct inversion scheme has the samples of the scattered field as input and provides an estimate of unknown complex permittivity profile maps as output.

The use of ANNs for imaging purposes goes back till to the nineties for simple imaging scenarios (Caorsi and Gamba, 1999), but nowadays has become more and more attractive due to the improvement in the computational power of modern technology as well as to the innovative network architectures proposed in the scientific literature. Most articles propose the use of machine learning either for the imaging of simple scenarios or as a complementary strategy in the inversion procedure for regularisation and super-resolution issues (Shah and Moghaddam, 2017)–(Ashtari et al., 2010).

In this framework, ANNs based on multilayer perceptrons could be very promising for online imaging purposes. Firstly, they act as universal function approximators, and secondly they prove to be robust in presence of noise and fast, since after a training step they are able to implement a direct mapping between data and unknowns without any analysis of the physical rules associated with these data.

Due to these interesting capabilities, they have been exploited for remote sensing (Vitale et al., 2019; Aghababaee et al., 2013) as well as for inverse scattering applications. Most of the research articles focus on the use of machine learning techniques in order to find a more stable solution, i.e. as an efficient regularisation (Shah and Moghaddam, 2017)-(Ashtari et al., 2010), as well as a hybrid strategy with some analytical information.

A critical issue in the use of ANNs resides in the choice of a properly large data set for the training of the network, since it is fundamental for the estimation of its weights. After an initial training procedure, which represents the bottleneck of this kind of approaches due to the required computational burden, a direct mapping between data (i.e., the scattered field samples) and unknowns (i.e., the geometrical and dielectric features of the targets) can be obtained, which speeds up the imaging procedure considerably.

In this manuscript, the authors want to propose an ANN architecture in order to provide a quantitative online imaging of the electric properties of female breast tissues starting from measures of the scattered field. The universal approximation theorem (Hornik et al., 1990) states that any arbitrary nonlinear function can be approximated via a proper network architecture. Based on it, in this manuscript a three-layer network is proposed. Each hidden layer combines all of the features (local information) learned by the previous layers across the image to identify the largest patterns. Fig. 2 provides a sketch of the considered ANN architecture.

4 NUMERICAL BREAST PHANTOMS GENERATION

The selection of a proper training data set is of relevant importance for the learning procedure since the choice of the weights involved in the network is strongly related to the considered pairs in the data set. As a matter of fact, large pairs of scattered data and reference profiles are required to build a data set which is relevant in order to obtain good recovery performance. To this aim, a numerical 2D randomly-shaped breast profile generator has been exploited in order to create the reference profiles, and the forward problem has been implemented in order to create the related scattered data, obtaining the training data set required by the network.

Due to the relatively simple geometry of the breast shape, and since the biological tissues can be mainly grouped into fibro-glandular, transitional and adipose tissues (Lazebnik et al., 2007), the authors proposed an automatic numerical breast generator which allows to obtain ellipsoidal-shaped phantoms with a variable percentage of fibro-glandular internal tissue. The skin thickness is modelled as a uniform random variable in the range $[1.5, 2.5]$ mm whose dielectric permittivity is equal to 36 and conductivity to 0.86 S/m. Regarding the complex permittivity of the breast inner tissues, the statistical distributions reported in (Lazebnik et al., 2007) have been considered.

In order to model the spatial variability of the

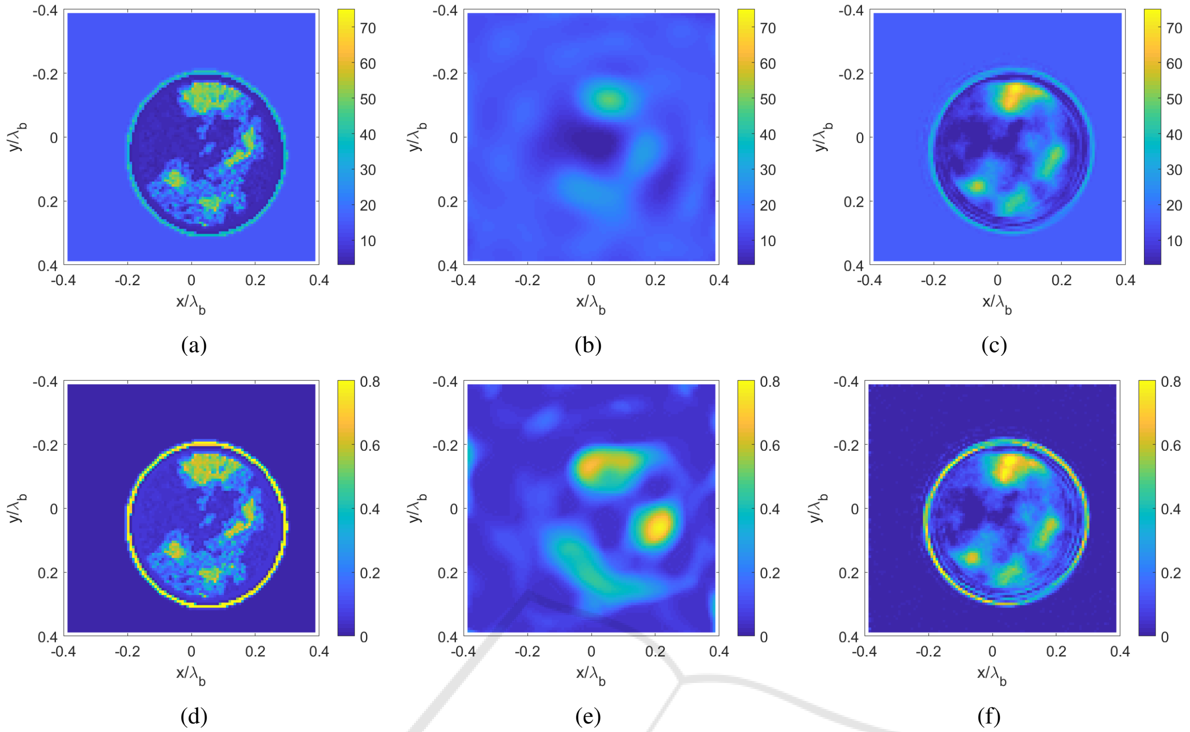

Figure 3: Numerical results (a),(d) real and imaginary parts of the reference complex permittivity, respectively; (b),(e): retrieved profiles via a classical non-linear approach (distorted-Born iterative method) and (c),(f) via the proposed neural network architecture.

fibro-glandular tissue, a random-shape generation based on a universal multi-fractal random field generator proposed in (Schertzer and Lovejoy, 1989) has been adopted. The profile generator can be controlled via setting three different parameters which govern the level of sparsity of the fibro-glandular tissue as well as the ruggedness or smoothness of the profile.

5 NUMERICAL RESULTS

The scattered field related to the numerical breast phantoms was evaluated via a method of moments (MoM) forward solver. This information was exploited for the training phase of the network. To test the performance of the proposed ANN, 50.000 breast profiles were generated and split into training (80%), testing (15%) and validation (5%) data sets.

The ANN architecture proposed in Section 3 was trained by employing the stochastic gradient descent algorithm with momentum which updates the network parameters by taking small steps in the direction of the negative gradient of the loss. The default values of the initial weights belong to a Gaussian distribution with zero-mean and standard deviation equal to 0.01, and initial bias equal to zero. Finally, a regularisation term for the weights of the loss function is added to reduce the overfitting.

Regarding the geometry of the problem at hand, the investigated area is 15 cm^2. The matching fluid employed as background medium is lossless with $\varepsilon'_{r,b} = 15$ in order to maximise the matching with the skin layer and, thus, the amount of field reaching the breast internal tissues (Catapano et al., 2010).

The operating frequency is fixed at 1 GHz and the circle on which the receivers and transmitters are located has radius equal to 22.5 cm. Regarding the number of antennas, thirty elements acting as transmitters/receivers in a multiview-multistatic fashion have been assumed. Reconstruction results related to one case are reported in Fig. 3 in comparison with classical distorted-Born iterative method (DBIM) estimation.

6 CONCLUSION

In the this paper, a novel and computationally fast approach based on ANNs for the quantitative microwave imaging of breast tissues has been presented. A preliminary performance assessment was proposed in a simplified 2D scenario which can be easily generalised to the more complete and realistic case of three-dimensional breast.

In the framework of imaging techniques, microwave-based tomographic breast imaging may represent a valid alternative or a complementary medical exam, since it is safe compared to the standard mammography and less expensive rather than magnetic resonance imaging.

For the generation of the training data set, a randomly-shaped breast profile generator has been proposed whose tissues electric parameters were selected according to proper statistical distributions as reported in the scientific literature (Lazebnik et al., 2007). Regarding the network design, a three fully-connected layers network architecture was proposed and compared with a classical inversion scheme (DBIM). It is worth to underline the capability of the proposed approach to retrieve the imaginary part of complex permittivity with a good accuracy compared with classical approaches, as well as the capability of correctly estimating the thickness of the skin layer.

Future work will focus on testing new network architectures and on the proper design of the training data set.

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