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A SVM-based approach to microwave breast cancer detection

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Abstract

Early breast cancer detection is of crucial importance: this form of cancer is the second most common cause of death among women due to malignant tumors, whereas early detection leads to longest survival or even full recovery. Conventional X-ray mammography possesses a range of shortcomings and new techniques must be developed. Features of microwave breast imaging make it an attractive alternative. The aim of the present work is to propose a 3-D approach based on support vector machine classifier whose output is transformed to a posteriori probability of tumor presence. Like confocal microwave imaging introduced by S.C. Hagness et al., the present approach is aimed at detecting tumor locations directly, avoiding solving computationally extensive inverse scattering problem. Microwave data have been generated using finite element method with impedance boundary conditions. Noisy environments have been considered as well. The obtained probability maps demonstrate that the region around the tumor location usually clearly stands out against the background of overall probability values.

Keywords: Support vector machines; Breast cancer detection; Microwaves

1. Introduction

Relevance of breast cancer detection is evident: this type of cancer represents the second most common cause of death among women due to malignant tumors. Yet, if the detection is done in the early stage, the longest survival or even full recovery is achieved. Unfortunately, such early detection is still a challenge, and breast cancer remains the only one type of cancer with a positive growth rate over the last years.

Currently, X-ray mammography represents the gold standard method of breast imaging. Other methods, including magnetic resonance imaging and ultrasound approaches, are as yet either less effective or too expensive for mass-screening purposes. X-ray mammography is based on the fact that tumor tissue exhibits microcalcifications, which affect mammogram formation. Mammogram is 2-D map that represents the intensity of X-ray radiation passed through the previously compressed breast (in order to reduce image blurring and to reach uniformity of tissue). However, relatively small contrast between affected and normal tissue for X-rays leads to sufficiently high false-negative (4–34%) and false-positive (70%) rates (Fear et al., 2002). Besides this, very early stage tumors do not necessarily exhibit microcalcifications. One should also notice that ionizing radiation is accumulated over repeated scans.

Microwave imaging approaches to early breast cancer detection offer an attractive alternative to conventional mammography. Their attraction is motivated by dielectric-property contrast between normal and malignant breast tissue at microwave frequencies (between 2:1 and 10:1) (Hagness et al., 1998). Microwave imaging does not require uncomfortable or painful breast compression, and furthermore, it avoids exposure of a patient to ionizing radiation: the level of radiated microwave power could be lower than that from a typical cell phone. Whereas mammograms are 2-D projections, microwave imaging techniques provide 3-D images of the breast tissue. Finally, unlike X-ray mammography, microwave imaging allows easy access to the upper outer quadrant of the breast, where almost 50%

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of cancers occur. A brief introduction can be found in Fear et al. (2003).

Currently, three directions in microwave breast imaging can be distinguished: hybrid microwave-induced acoustic imaging, microwave tomography, and ultrawideband (UWB) radar techniques (Davis et al., 2005). In the first direction microwaves are used to heat (and, thus, expand) tumors; pressure waves generated in such a way are then detected by ultrasound transducers. Microwave tomography consists in recovering dielectric-properties profile on the basis of measurements of narrow-band microwave signals transmitted through the breast. This type requires solving both forward scattering problem and nonlinear ill-conditioned inverse scattering problem iteratively, until the computed and the measured data are close enough (e.g. Bulyshev et al., 2001; Zhang et al., 2003).

UWB radar technique has been introduced by S.C. Hagness in 1998 (Hagness et al., 1998, 1999). The technique adapts ideas of ground penetrating radar. The aim is to estimate the energy reflected from any point chosen inside the breast, without reconstruction of the breast's dielectric-properties profile. The key point of the technique is *time shifting and summing* (synthetic focusing) of scattered waveforms. In the last years S.C. Hagness and colleagues have presented further development of UWB radar approach which improves the process of scattered energy estimation, namely *Microwave Imaging via Space-Time Beamforming* (MIST) method in both time and frequency domains (Bond et al., 2003; Davis et al., 2003).

In this paper, authors propose to tackle three-dimensional breast cancer microwave detection problem using *Machine Learning* framework, namely, the support vector machine (SVM) (Vapnik, 1999; Scholkopf and Smola, 2002) classification technique with generation of tumor-presence probability map (risk map). SVMs are sufficiently new techniques for classification and regression estimation tasks. Being proposed in the 1990s, they have demonstrated excellent results in a wide range of problems (hand-written text recognition, electricity load prediction, biomedical engineering, face recognition and face detection, etc.). In contrast to the conventional artificial neural networks (NNs), SVMs are based on profound theoretical foundation (statistical learning theory) with well-defined generalization property (Vapnik-Chervonenkis dimension) (Vapnik, 1999) and do not suffer from the curse of dimensionality. Besides, upon SVM training phase, constrained quadratic optimization problem (CQP) is to be solved, that can be approached by means of fast sequential minimal optimization (SMO) algorithm proposed by Platt (Platt, 1999a; Chang and Lin, 2005). The other advantage is that unlike optimization problems arising upon NN training, CQP has unique solution, and hence, does not suffer from local minima.

The microwave backscatter data used in the present work have been generated by means of the finite element method. In order to formulate the problem under classification framework, the domain under investigation has been split into a grid of cells. Each cell has been classified, and then assigned the corresponding tumor-presence probability value. Mapping SVM outputs to the probability space has been carried out using the approach proposed by Platt (1999b). This approach does not require modification of SVM structure and, hence, preserves sparseness of SVM. Both noiseless and noisy scenarios have been considered.

The proposed approach is in a certain sense original for microwave breast sensing. It adopts ideas from both tomography and UWB radar techniques. Like in the former, monofrequency microwave signals are used for sensing. The approach does not imply conventional solving inverse scattering problem and recovering dielectric properties profile as well. Instead, like UWB radar techniques, it aims at detecting tumor locations directly.

Authors have already demonstrated application of SVMs to microwave buried object detection in 2-D by means of support vector regression (Bermani et al., 2003, 2004, 2005; Caorsi et al., 2003). However, the regression approach becomes inapplicable when scenarios with multiple scatterers are to be considered. Classification approach used in present work lifts this restriction. Nevertheless, single tumor (i.e. scatterer) scenarios are considered at the moment. Besides, the present work concerns 3-D rather than 2-D.

The paper is organized as follows. Section 2 presents an overall description of the proposed approach, touching upon both electromagnetic and machine learning aspects. Section 3 is dedicated to brief explanation of SVM classification technique and mapping of SVM outputs to probability space. The way the breast has been modeled and the electromagnetic data have been obtained is described in Section 4. The results for both noisy and noiseless environments are presented and discussed in Section 5. In conclusion, Section 6 reports some final remarks and directions of the future work.

2. Approach description

Let us consider a patient oriented in a supine position, when the breast is naturally flattened. Such a position provides easy access to the quadrant near the armpit, where almost 50% of cancer occur, and where the breast is less than about 2.5 cm deep (Hagness et al., 1998; Li and Hagness, 2001). The breast is illuminated by T transmitters emitting monochromatic electromagnetic wave of frequency f (Harrington, 1961), and the scattered field is collected by R receivers, both located above the breast (Fig. 1).

Since the breast tissue can be considered with high order of accuracy as a linear media, the received signals are monochromatic, at the same frequency f (Harrington, 1961). This fact allows one to describe them in terms of complex amplitudes (Clemmow, 1973) (for comparison, in UWB approaches received signals are converted to sampled waveforms). Let column vector

$$\mathbf{E}_{tr|rs} = (E^{\mathrm{Re},x}_{tr|rs}, E^{\mathrm{Im},x}_{tr|rs}, E^{\mathrm{Re},y}_{tr|rs}, E^{\mathrm{Im},y}_{tr|rs}, E^{\mathrm{Re},z}_{tr|rs}, E^{\mathrm{Im},z}_{tr|rs})^{\mathrm{T}} \tag{1}$$