SVM-based Classification of Breast Tumour Phantoms Using a UWB Radar Prototype System

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Abstract

In this paper, a follow-up study exploring the classification of phantoms mimicking benign and malignant breast tumours, using a pre-clinical Ultra Wideband (UWB) prototype imaging system, is presented. A database of 13 benign and 13 malignant tumour phantoms was created using material which mimicked the dielectric properties of tumour tissues in the 1-6GHz frequency range. The classification was performed using a machine learning algorithm – Support Vector Machines (SVM) – and the results were compared to those of a previous study by the authors where Linear Discriminant Analysis and Quadratic Discriminant Analysis were considered.

1. Introduction

Breast cancer is one of the most significant health problems in modern society. In 2008, GLOBOCAN reported 1,384,155 new cases and 530,232 deaths caused by breast cancer [1, 2]. The key factors in improving both survival rates and quality of life for cancer patients are: reliable diagnosis for early detection, early intervention and reliable monitoring. X-Ray mammography is the gold standard for breast screening; however this technology has well-known limitations in terms of sensitivity and specificity which lead to false positive and false negative rates, as high as 75% and 34%, respectively [3].

Microwave Imaging has been proposed in the context of breast cancer for both imaging and, more recently, classification of benign and malignant tumours [4-6]. Microwave Imaging techniques often involve the use of one (or several) microwave waveforms which illuminate the breast, while resulting backscattered waves are recorded in one or more antennas [7]. The backscattered microwave signals carry information that can be used to reconstruct a reflectivity map of the structures in the breast region in order to detect any malignancies present. Furthermore, the backscattered radar signals carry information on the radar target signature of tumours which can be used to classify tumours as benign or malignant.

The authors have previously examined the potential of classification algorithms to help determine whether a tumour is benign or malignant in several simulated scenarios [5, 6]. In previous studies, Conceição *et al.* [5, 6] created a tumour database comprising 480 breast tumour models of 4 different sizes and 4 different shapes based on Gaussian Random Spheres [8]. In these studies, several Feature Extraction Methods (FEMs) were tested: Principal Components Analysis (PCA), Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT) combined with a range of classification algorithms: Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis, machine learning classifiers such as Support Vector Machines (SVM).

Alshehri *et al.* [9] first presented a study in which they classified benign and malignant breast tumour phantoms based on the different dielectric properties between the two tissues, using the newly established dielectric properties published by Lazebnik *et al.* [10]. However, since the dielectric properties between the two types of tissue can overlap, the authors proposed a classification algorithm which will take into account the size and shape of tumours, which are known to reflect the nature of tumours. In a previous study [11], the authors have completed an initial study in which they classified benign and malignant tumour phantoms using a UWB pre-clinical radar prototype. To

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the best of our knowledge, this was the first study to report experimental results using a pre-clinical UWB prototype imaging system for tumour classification based on the shape of tumours. The study in [11] has been expanded by using SVM as a classification algorithm, and this paper compares these results to those previously obtained by using LDA and QDA.
The remainder of the paper is organized as follows: the experimental setup and materials used are described in Section 2, the methodology for data acquisition and data post-processing are presented in Section 3, the results are shown in Section 4, and conclusions and future work are discussed in Section 5.

2. Experimental Setup and Materials

The breast microwave radar pre-clinical prototype developed in the University of Manitoba, Canada, was used in this study. The system consists of a Vector Network Analyser (Field Fox N9923A, Agilent Technologies), an in-house developed Vivaldi antenna (two layers of Arlon-Diclad 527, and has a permittivity of 2.65 and loss tangent of 0.0022) which was connected to the VNA via a 50 Ω cable and was attached to a wall in the interior of a plexiglass tank filled with canola oil. The system is illustrated in Figure 1 (left), and is described in detail elsewhere [12].
The plexiglass tank was filled with a coupling medium, canola oil, which was found to be a suitable match to the impedance between the antenna and the breast phantom [13]. The dielectric permittivity of glycerin mimics the average values found in low density breast regions [14], as can be seen in Figure 1 (right), and the breast was simulated using a styrene-acrylonitril cylinder with a diameter of 13 cm and a height of 35 cm filled with glycerin. Tumour phantoms were simulated with a mixture of TX151 solidifying powder in a volume proportion of 6:1 of water to TX151 powder.

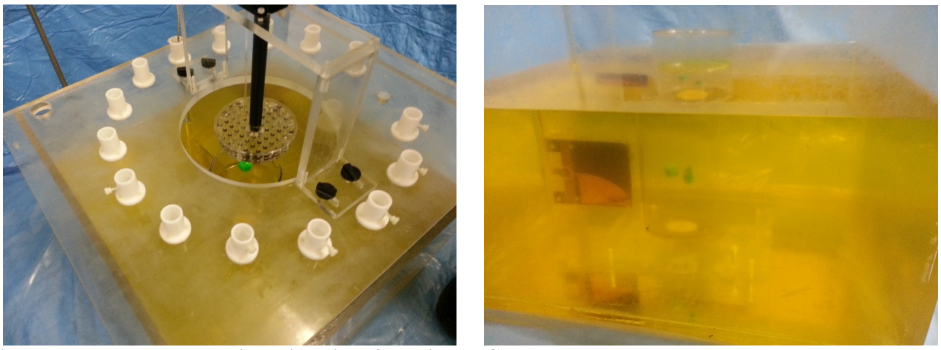

Figure 1: Breast microwave radar prototype in University of Manitoba, Canada.

3. Methodology

3.1 Data Acquisition

All datasets used in this study were recorded using a monostatic scan protocol, in which a single antenna was used as a transceiver. To emulate a circular scan geometry, the phantom was attached to a motor which was rotated in angular increments of 2.5º, recording 144 measurements for each combination of breast phantom and tumour. The radius of the scan geometry was 21cm. Thirteen malignant and thirteen benign tumour models, which are partially shown in Figure 2, were tested with the breast phantom, and similarly to [11], a total of 3744 backscattered signals were recorded for use with the classification algorithm,.

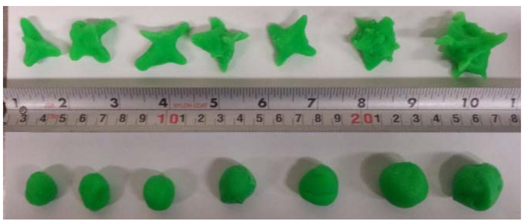

Figure 2. Subset of the malignant (top) and benign (bottom) tumour models used in this study.

The average diameter of the tumour phantoms varied between 13 and 40 mm, and their shape was modelled to match the Gaussian Random Sphere models that the authors had used in previous simulation studies [5, 6]. As mentioned, the phantoms were built with a mix of water and TX151 powder (on a proportion of 6:1) so that the dielectric properties of the phantom material would mimic the dielectric properties of breast tumour tissues [10] in the frequency range between 1 and 6 GHz that was used in this study.

3.2 Data Post-Processing

The backscattered signals were recorded in the frequency domain, and then converted to the time domain using the Inverse Fast Fourier Transform. Principal Component Analysis was applied to the signals in order to extract the most relevant features from each of the 3744 signals. A subset of 13 principal components was selected, following the same method as [15] so that unnecessary computational complexity could be avoided while maintaining high classification accuracy.

The classification algorithm Support Vector Machines, fully described in [5], was used and compared to the results obtained with the Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) obtained in [11]. The classifiers were tested using a K-fold cross-validation method to ensure that the training and testing groups for the classifier were treated independently, and overfitting could be avoided. The data was divided into 13 (*K*) groups for cross-validation, with each group comprised of 144 signals from 2 different tumours. The performance for the SVM-based classification architectures depends on optimal values for parameters γ and C, as described in [11]. For the results presented here, the optimal SVM parameters are as follows: $\gamma=2^2$ and $C=2^3$.

Each signal was classified as either benign or malignant, and so classification followed a Coarse-Shape architecture.

4. Results

The classification accuracy obtained with SVM was obtained and compared to the results in [11] with LDA and QDA. The classification of the Coarse-Shape classifier is shown in Table 1. In this study, the reflected signals are treated independently, i.e. there is no record of which of the 144 recorded reflected signals belongs to the 26 tumours. Thus, in order to maximise the size of the dataset for testing purposes, each reflection was treated as a separate test for the classifier.

Table 1: Classification performance for a Coarse-Shape classification architecture using LDA, QDA [11], and SVM.

Classification method	Linear Discriminant Analysis (in [11])	Quadratic Discriminant Analysis (in [11])	Support Vector Machines
Performance of Coarse-Shape classifier	87.10%	89.34%	90.95%

5. Conclusions and Future Work

The capabilities of a SVM-based classification algorithm to classify benign and malignant breast tumour phantoms, based on their RTS, have been examined. Results presented here have shown that SVM allowed for improved classification accuracy, outperforming both LDA and QDA, which follows the same tendency observed in previous simulated results [6]. Overall, SVM outperformed LDA by 3.85%, and QDA by 1.61%.

In the future, the potential to combine classification results from each angular position around the breast will be considered. Also, classification of tumour phantoms in heterogeneous (and hence more realistic) breast phantoms will be considered.

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