A Novel UWB Imaging System Setup for Computer-Aided Breast Cancer Diagnosis

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***Abstract*—Microwave imaging using UWB radar has been proved as a promising technique for breast cancer diagnosis. However, most of the researches in this domain are based on simulated environment, due to the fact of complex system setup. Few groups have built up an actual UWB imaging system for real life experiment. In this paper we present a novel UWB imaging system setup for breast cancer diagnosis. The system consists of one horn antenna as the transmitter, and a 4-element linear planar antenna array as the receiver to collect the backscattered signal. Based on this system setup, we propose a data-driven approach using linear classifier to detect tumor presence and further explore tumor characteristics, without constructing the UWB image. This approach bypasses the complicated image reconstruction algorithm and ill-posed inverse problem. With the low complexity system setup, our data-driven approach gives promising results in the breast cancer diagnostic experiment. The experiment shows that this system setup can be adopted as a prototype for research project in computer-aided diagnosis of breast cancer.**

***Keywords*—UWB imaging system, breast cancer, computer-aided diagnosis, linear classifier**

I. INTRODUCTION

In recent years, many researchers have investigated the method of employing UWB radar to detect breast cancer. Successful works have been proposed using numerical breast model in FDTD simulations [1-2]. Experimental works using breast phantom have also been reported in [3-6]. The key to a successful detection is based on the fact that the breast tumors have dielectric properties that are greatly different from those of healthy breast tissues. The UWB signals are transmitted into the breast, and the backscattered signals are recorded and processed to find out the tumor's presence.

However, the UWB microwave imaging technique does not provide high enough resolution to reconstruct the fine spatial features of a detected lesion in the breast. Confocal Microwave Imaging (CMI) technique [1] applies delay-and-sum (DAS) beamforming to reconstruct the image. This technique has the advantage of simplicity in image reconstruction process, but it offers limited performance in terms of image resolution and clutter rejection. Microwave Imaging via Space-Time (MIST) algorithm [4] has addressed these limitations and outperformed DAS using data-independent algorithm. Other techniques include Tissue Sensing Adaptive Radar (TSAR) imaging [5], and time reversal method in microwave imaging. For all these methods, the general idea is to process the backscattered signal through a specific image reconstruction algorithm to obtain knowledge of the breast tumor. UWB image reconstruction is an inverse problem which is ill-posed and challenging due to the nonlinear nature of the problem itself. Thus it requires complex system setup and sophisticated algorithm to solve such problem. Alternatively, we could bypass the image reconstruction process and use data-driven approach to obtain information about the breast tumor directly, i.e. information regarding the presence of the tumor.

Sardar and Mishra [7] proposed a method called Application Specific Instrument (ASIN) framework for the diagnosis of breast cancer. They applied radial basis function based neural network to perform a pattern recognition task to determine whether the tumor is present or not. If the answer is positive, they further estimate the size of the tumor through regression machine, again, with the use of RBF based neural network. But they didn't give a complete solution, as their results were only based on simulated data and not validated with real life experimental data. Alshehri et al [8] built a UWB imaging system to detect tumor in breast phantom. The system consists of commercial UWB transceivers and neural network based pattern recognition software. However, such commercial UWB transceiver is hard to configure to adapt to various experimental environments, thus not practical for laboratory use. Moreover, if we could locate the proper features related to the target signature – tumor characteristics, we do not need a sophisticated machine learning tool – neural network to solve the breast cancer diagnosis problem. A linear classifier is capable for the work. We will demonstrate this idea in our experiment in section IV.

Once the presence of tumor is determined, we could gather more information related to the tumor's characteristics. Davis et al [9] presented a data-driven approach for breast tumor characterization based on UWB backscattered signals. Linear classifier is applied to distinguish tumors with different shape and size. Their results are encouraging but only tested in simulation. We design an experiment to explore the tumor characteristics with our system setup. The preliminary result verifies the feasibility of such data-driven approach.

In this paper we first propose a novel UWB imaging system setup for breast cancer diagnosis. The transmitter consists of a trigger, a pulse generator and a single horn antenna. On the receiver side, the backscattered signals are collected by a linear planar antenna array, sampled by data acquisition unit with high sampling rate (40 GHz), and post-processed in a computer for diagnostic purpose. This system setup is simple and cost

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effective. It could be configured quickly to adapt to any UWB radar based breast cancer research project or served as a prototype of UWB imaging system for computer-aided breast cancer diagnosis.

Based on our system setup, we investigate how the data-driven approach could be adapted in breast cancer diagnostic experiment using homogeneous breast phantom. We describe a linear classifier based scheme in breast cancer diagnosis. The diagnosis operates in two stages. In the first stage, it detects whether a tumor is present or not inside the breast phantom. If it is determined that the tumor is present, the second stage is performed to explore the tumor characteristics.

This paper is organized as follows. The system setup is presented in the next section, followed by the diagnosis procedure in section III. The experimental results are presented in section IV. The conclusion and future work discussion are given in the last section.

II. UWB Imaging System Setup

The proposed UWB imaging system setup consists of three main parts: breast tissue and tumor model, UWB transceiver and computer aided diagnostic program. We describe the first two parts in this section and the third part in section III.

A. Breast Tissue and Tumor Phantom Construction

In the study of breast phantom, the most important metrics is the dielectric difference between the normal breast tissues and the malignant tumor. Previous studies in dielectric spectroscopy suggest that the dielectric properties contrast between malignant and normal breast tissue is greater than 2:1 in the microwave frequency range [4]. In our experimental setup, soybean oil with dielectric constant $\varepsilon_r = 3.0$ is chosen as the normal breast tissue simulant due to its similarity in dielectric properties to low-water-content fatty tissue [4]. The soybean oil is contained in a tube made of acyclic ($\varepsilon_r = 1.9$), which simulates the skin layer. Aluminum block wrapped by aluminum foil ($\varepsilon_r = 9.3$) is hanged inside the oil to represent the tumor.

B. UWB Transceiver Design

The UWB antenna used for transmitting the pulse is a large double-ridged horn antenna, as shown in Figure 1 and 2. It has low return loss in the frequency range of 0.8 to 18 GHz and has an average gain of 12 dBi which is high enough to guarantee the signal to be able to penetrate the breast model [10].

Figure 1: Double-edge horn antenna [10]

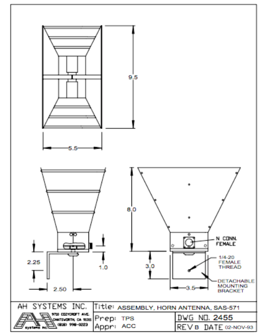

Figure 2: Double-edge horn antenna mechanical drawing [10]

At the receiver side, we design a checker-shape planar antenna as shown in Figure 3 and 4. It is small enough to be easily attached to the surface of the breast model. The antenna's return loss is under -10dB in the frequency range of 3 to 15 GHz, which meets the experimental requirement [11].

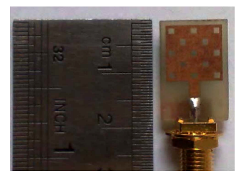

Figure 3: Checker-shape planar antenna [11]

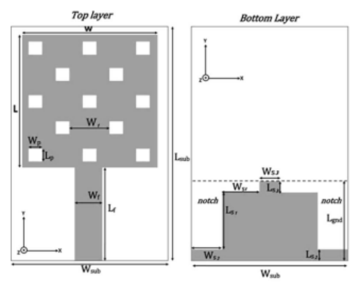

Figure 4: Checker-shape planar antenna mechanical drawing [11]

A 4-element linear array based on the check-shape planar antenna is developed to capture the backscattered signals, as shown in Figure 5. This linear array setup has simple arrangement, and offers better temporal-spatial resolution than a single antenna.

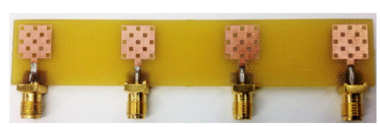

Figure 5: Linear antenna array

A pulse with 70 ps width is created using the PSPL 3600 pulse generator, as shown in Figure 6. This UWB pulse is used to excite the breast model.

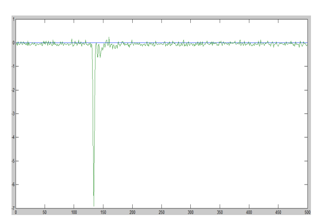

Figure 6: Pulse for excitation

The backscattered signals collected by the receiver antenna array are acquired by a 4-channel high sampling rate oscilloscope-Tektronix TDS6154C, as shown in Figure 7.

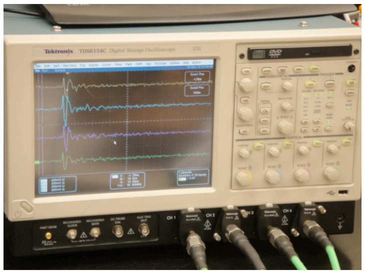

Figure 7: The backscattered signals display on the screen

Overall, the UWB transceiver setup and block diagram are shown in Figure 8 and 9, respectively. It consists of the following:

- Trigger: Wavetek, Arbitrary Waveform Generator
- Pulse generator: PSPL 3600, with 70 ps duration
- Transmitter: single big horn antenna
- Receiver: 4 element checkered-shaped antenna array
- Data acquisition: Agilent Oscilloscope, with 40 GSa/s

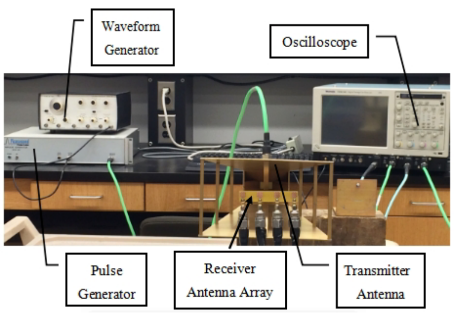

Figure 8: UWB transceiver setup

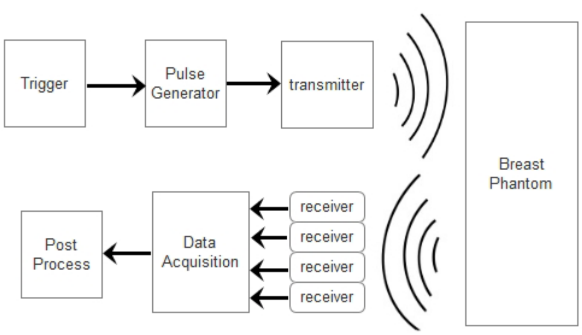

Figure 9: The UWB transceiver block diagram

III. Diagnostic Procedure

The computer-aided diagnosis of the breast cancer operates in two stages. In the first stage, a binary classifier is constructed to detect whether the tumor is present or absent within the breast tissue. Once the answer is positive, the second stage is initialized to analyze the tumor's shape and size. Multi-way classifiers are developed to classify the tumor with different physical characteristics, including shape and size. The general procedure is illustrated in Figure 10.

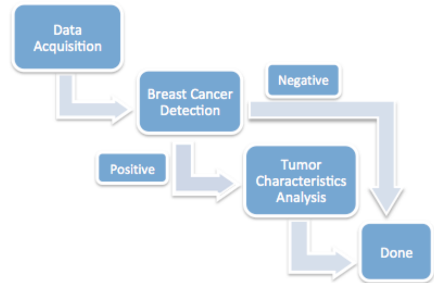

Figure 10: Computer-aided diagnosis procedure

The diagnosis is done through identifying which class a backscattered signal belongs to base on the observation data. To achieve this goal, we need to extract features from the data that are good discriminants among the C classes, where C is the total number of class. In our experiment, C equals 2 in the first stage, equals 3 in the second stage. The feature extraction is based on a set of labeled training data $\{X_i, y_i\}_{i=1}^{M}$, where X_i is the input vector containing the measured data for the i^{th} target realization and $y_i \in \{1, 2, \ldots, C\}$ specifies which class the i^{th} target belongs to.

The classifier is designed as a three-step procedure as follows:

First, we construct the training set. The time domain samples collected by the linear antenna array served as the input vector X in the training set. The target value y is defined as the label of classes.

Second, we perform principle component analysis (PCA) to reduce the feature space dimension, and select the dominant features for the classification purpose. This is achieved by applying singular value decomposition (SVD) to project the signals to low dimensions. Specifically, if we have N samples, each sample is a time domain received signals with M entries. We form a matrix $A \in \Re^{N\times M}$, carry out the SVD, $A = \overset{N\times M}{U}\ \overset{M\times M}{\Sigma}\ V^T$, and truncate it to dimension of 2. Then the components $U_k \Sigma_k$ with $k = 2$ are 2D vectors with N data entries. These 2D points can be plot on a plane to visualize the data.

Third, once the good features are selected, we could build a linear classifier to fulfill the classification work. The commonly used linear classifier, such as K nearest neighbor (KNN), linear discriminant analysis (LDA) or Naïve Bayes could be implemented in our classifier and they all achieve good classification result.

IV. Experimental Results

In this section, we present the experimental results of the two stages breast cancer diagnosis.

A. Tumor Detection

The first stage is to detect whether or not a tumor is present within the breast tissue. This is a binary classification problem. The breast phantoms with and without tumor are both illuminated by the transmitter. Backscattered signals are collected by the receiver antenna array. As the distances between the antenna and the breast phantom are known beforehand, we are able to do a simple time gating to preserve the expected tumor response. As shown in Figure 11, for a single backscattered signal, the tumor response is located at the secondary peak of the entire time samples.

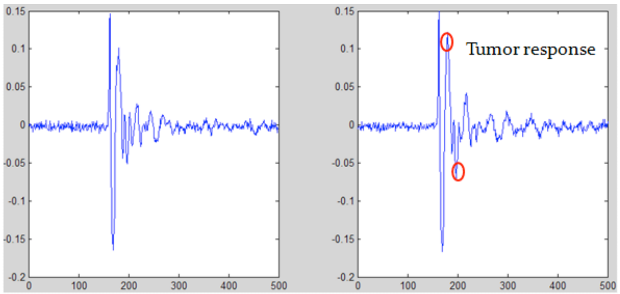

Figure 11: Tumor response in a single backscattered signal

The total response of the phantom includes skin response and tumor response. To remove the skin response from the signal, we performed time gating using knowledge of the distance between antenna and phantom. After performing time gating, we construct the input vector for the training set. Figure 12 shows backscattered data vectors with and without tumor. Each vector contains 4 concatenated time-series signal corresponding to the 4-elements antenna array. From this individual observation, we could expect different signal signature in terms of tumor presence. This leads to correct pattern recognition, in other words, correct tumor detection.

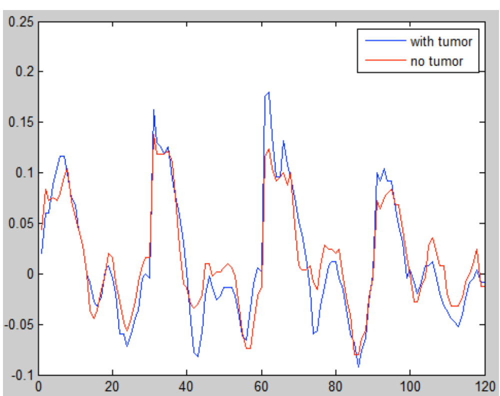

Figure 12: Space-time samples

The input waveform forms the original feature space for the classifier. The next step is to perform dimension reduction using PCA, to find the dominant feature of the target signature. Figure 13 shows an example of the 2-D discriminant space from the PCA-based dimension reduction for tumor detection. We could see the training points form two clusters corresponding to the two classes, with and without tumor, respectively. The two test points lie within two different clusters suggesting the correct classification result.

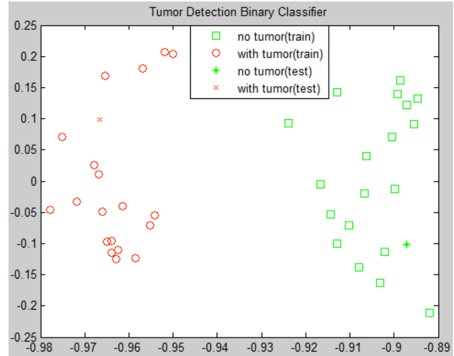

Figure 13. Discriminant space visualization for tumor detection

A total of 20 readings are taken for breast phantom with tumor and another 20 readings are taken for breast phantom without tumor. K-fold validation with K = 10 is applied for training and testing of data using the linear classifier. Figure 14 shows the binary classifier performance as a function of SNR. LDI classifier is selected as the linear classifier. The Additive White Gaussian Noise (AWGN) is added to the backscattered signal manually. This figure demonstrates the robustness of the linear classifier, as the Misclassification Rate (MCR) drops to below 1% when SNR = 9 dB.

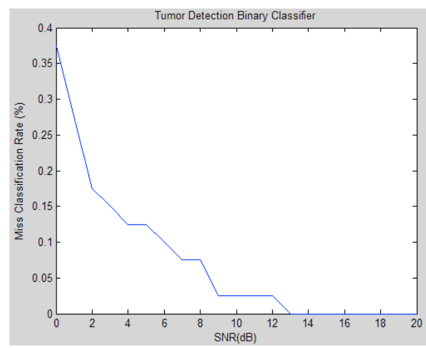

Figure 14: MCR-SNR curve

Thus, this preliminary experiment proves the feasibility of applying linear classifier in the detection of breast tumor. Once we have determined the presence of tumor within the breast tissue, we could move to the second stage to estimate the characteristics of the tumor.

B. Tumor Shape and Size Classification

In a clinical environment, to determine whether a tumor is benign or malignant, it is important to understand the characteristics of the tumor. Without image reconstruction, linear classifier lacks capability of providing exact shape and size information of the tumor. To extract as much information as we can, we develop multi-way classifiers to distinguish tumor with different shape and size.

In order to experimentally test if the classifier could correctly characterize tumor with different shape and size, aluminum blocks are used to simulate the tumor, as the aluminum is easy to carve. In order to better examine the tumor characteristics, samples are collected in 4 directions by the 4-element antenna array. In total we have 16 spatial samples, which are concatenated into one feature vector. Each spatial sample contains 30 time domain sampling points. The time samples are extracted from a time gating window containing the expected target backscattered signal.

As the time domain backscattered signal contains the target signatures, we are expected to be able to classify the physical characteristics of the target using multi-way classifier. The general procedure is the same as the binary classifier discussed in the first stage. In the tumor size and shape classification experiment, we test spheres with different diameters and different shapes with similar volumes, respectively. Figure 15 visualizes the size and shape discriminations of tumor.

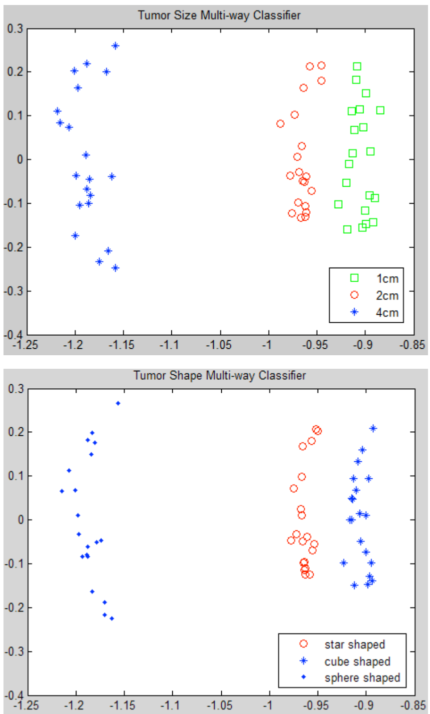

Figure 15: Discriminant space visualization for size/shape classification

Overall, the experimental results are promising. It illustrates the feasibility and advantage of using linear classifier in the computer-aided diagnosis of breast cancer based on UWB imaging system.

Due to the difficulty in constructing a reliable heteogeneous breast phantom, we have just considered homogeneous breast phantom. Also, we have assumed situation with only a single tumor. So the experiments and results presented are still in the preliminary stage. These restrictions are expected to be removed in future experiments.

V. Conclusion & Future Work

We have established an experimental UWB imaging system for breast tumor detection and characterization. This setup has low system complexity, which is easy to realize in the laboratory environment and could serve as a computer-aided diagnosis prototype in breast cancer research project. Using this simple system setup, the detection result based on linear classifier is promising, which successfully indicates the presence of the tumor. We further explore the possibility of using the linear classifier to distinguish tumor with different size and shape, the preliminary experimental result shows the feasibility of this idea.

We will keep working on this prototype system and the expected future works include: development of heterogeneous breast phantom and construction of better transceiver system for backscattered signal collection.

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