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Breast Tissue Characterization Based on Ultrasound RF Echo Modeling and Tumor Morphology

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Abstract—**We propose Fractional Differencing Autoregressive Moving Average (FARMA) process for modeling RF ultrasound echo. Along with the FARMA model parameters, we use several morphological features extracted from suspected tumors and patient age as potential indicators of malignant or benign masses. Here, we present computerized methods to extract these features and proposed statistical classifiers for breast tissue characterization. We demonstrate the performance of the proposed tissue characterization method on several *in vivo* ultrasound breast images including benign and malignant tumors. The area of the receiver operator characteristics (ROC) based on 120 *in vivo* images obtained from 90 patients yields a value of 0.8941, which indicates that proposed tissue characterization method is comparable or better in performance than other methods reported in the literature.**

Keywords—**Breast cancer, fractional differencing model, RF echo modeling, statistical classification, ultrasound tissue characterization.**

I. INTRODUCTION

Breast cancer is currently the leading cause of mortality among women. Currently, X-ray is the primary imaging modality for breast cancer detection, but in many cases the findings are not sufficiently specific and subsequent diagnostic work is required. Limitations in X-ray mammography have motivated research in other imaging modalities, such as ultrasound, positron emission tomography (PET), and magnetic resonance imaging (MRI). Currently, breast sonography is the primary alternative to X-ray mammography especially when high-resolution, real time, and high-quality data is needed.

Many studies point out that high-quality ultrasound can aid radiologists to differentiate with greater degree of confidence between benign and malignant tumors detected by mammography. To improve the usefulness of ultrasound in early diagnosis of cancer reliable quantitative methods must be developed for extracting additional information from the ultrasound B-scan images and backscattered echoes, which give rise to the resulting speckle.

Statistical modeling of RF echo leads to quantitative information that can be utilized in distinguishing between benign and malignant lesions. Ultrasonic back-scattered echoes, also known as speckle, contain information of potential diagnostic value. Model parameters, related to number, spacing or type of scatterers can be the identifiers of the tumor types in breast [1], [2].

Another approach in ultrasound tissue characterization is based on quantitative features extracted from B-scan images [3]. Visual interpretation of images can be computerized in order to provide useful information for radiologists. By examining the features of an image one can have an opinion about the type of lesion under examination. Benign features include ellipsoidal shape, thin echogenic pseudocapsule, mild lobulation, and hyperechogenicity, whereas malignant features include angular margins, acoustic shadowing, spiculation, calcifications, microlobulations, duct extensions, branch patterns, marked hypoechogenicity, and a depth-to-width ratio greater than 0.8.

The focus of the research presented in this paper was to model the RF echo using fractional differencing autoregressive moving average model (FARMA) and utilize estimated model parameters in tumor discrimination. In addition to RF echo modeling, further goal is to extract sonographical features from B-scan images that have tumor discrimination value. These features include solidity of the tumor region, number of corners of the tumor boundary, and depth-to-width ratio of the tumor. The overall aim of this study is to combine all quantitative features, including patient information and perform computerized statistical classification of suspected tumors as malignant or benign, in an attempt to decrease the number of unnecessary biopsies. Additionally, we assess the cancer discrimination value of various combinations of the proposed quantitative features.

The paper is organized as follows. In Section II, we present the FARMA model of the ultrasound RF echo. In Section III, we present the parameter estimation methods for the FARMA model and experimental results on several ultrasound B-Scan images with benign and malignant tumors. In Section IV, we discuss the estimation of sonographic features from B-scan images. In section V, we give classification techniques and performance evaluations of these techniques. Finally, remarks and future directions are provided in Section VI.

II. FARMA MODEL FOR RF ECHO

In ultrasonic applications, the RF echo scattered from tissue is modeled as a convolution integral of the ultrasonic pulse and the scattering structure as follows:

$$y(n)=h(n)*x(n) \tag{1}$$

where $h(n)$ is the transducer response and $x(n)$ is the response tissue.

It was empirically observed by Onaral *et. al* [4] and Petropulu *et. al* [5] that the tissue response exhibits $1/f$

characteristics due to the complex structure of tissue scatterers. From the point of view of texture modeling, similar observations were also made for natural terrain and texture in remote sensing imagery [6]. In the later case, self-similar and long-term correlated time series models were successfully used to model and classify image texture. Fractional differencing (FD) model [7], [8] has a number of advantages as compared to other *1/f* models. Fractional differencing (FD) is a discrete, stationary process with self-similar and long-term correlated structure. It is governed by a long-term correlation parameter d, $0<d<0.5$. Recently, FD model was used to capture the self-similar nature of the network traffic. This process can be compactly represented as follows:

$$x(n) = (1 - z^{-1})^{-d} w(n) \tag{2}$$

where $w(n)$ is a white Gaussian noise sequence with zero mean and unity variance, and d is the fractional differencing model parameter. FD processes can also be viewed as an infinite order MA process:

$$x(n) = \sum_{k=0}^{\infty} f_k(d) w(n-k) \tag{3}$$

where $f_k(d)$ is defined by:

$$f_k(d) = \frac{d(1+d)(2+d).....(k-1+d)}{k!} \tag{4}$$

We model tissue response as a FD model and transducer response as an ARMA (p,q) model, which leads to FARMA modeling of the ultrasonic RF echo. FARMA process can be represented as:

$$A(z^{-1})x(n) = B(z^{-1})(1 - z^{-1})^{-d} w(n)\sqrt{\rho} \tag{5}$$

where z^{-1} is a unit delay operator, $A(z^{-1})$, and $B(z^{-1})$ are the autoregressive and moving-average polynomials of orders p and q respectively.

III. ESTIMATION OF FARMA MODEL PARAMETERS

We perform the estimation of FARMA model parameters in two steps: First, ARMA parameters of the transducer response are estimated, and next, the FD parameter of the tissue response is estimated.

ARMA parameter estimation is based on the transducer impulse response data, obtained using pulse-echo measurements from a flat surface reflector in water. The data was sampled at 20 MHz with 12 bits quantization after applying analog time-gain control. Prior to processing, RF data reflected from tissue was normalized and demodulated using base-band conversion techniques. This data set was used for model fitting and estimation procedures. The Final Prediction Error (FPE) criterion is used to estimate the order of the ARMA transducer response. The best model order for our transducer is an ARMA (3,1). The ARMA (3,1) parameters are estimated using the residual time series model.

Fractional differencing model parameter d of the tissue response was estimated from the FARMA process. The estimation procedure is based on the log-periodogram method [9] that uses a linear least square procedure. In order to estimate the fractional differencing parameter d, 120 different B-scan images from 90 different patients were used. 35 of these patients have malignant tumors and 55 of them have benign breast tumors. The B-scan (grey scale) breast images were obtained at the Radiology Department of Thomas Jefferson University Hospital Philadelphia, PA. For each B-scan image, 30 scanlines from inside and outside the of tumor region were taken with data lengths of 1x128, and each of these scanlines were used to estimate the fractional differencing parameter d. Hence, we have 30 values of d from inside and 30 values of d from outside the tumor sample. For each B-scan image, mean and variance of the fractional differencing parameter d were calculated for classification purposes. In Fig. 1, we present the mean values of the parameter d obtained from inside and outside the suspected tumor for 30 randomly selected patients.

IV. ESTIMATION OF B-SCAN IMAGE BASED PARAMETERS

In this study 3 sonographic features were extracted from the B-scan images. First two features are related to smoothness of the tumor region. According to radiologists' readings, if the tumor shape is smooth, in other words if it has a spherical/ovoid/lobulated/ellipsoidal shape, the tumor is expected to be benign. On the other hand, if the tumor has an irregular shape, it is expected to be malignant. Another decision criteria related to smoothness is the margin property. Unlike the benign regions with linear margins, malignant tumor regions have poorly defined angular margins. Here we identified the shape and margin of the tumor using two features: Solidity of tumor region and number of sharp corners of tumor boundary. Solidity of a region can be defined as the proportion of the pixels in the convex hull that are also in the region, and computed as: ***Area / ConvexArea.***

Image region solidity changes from 0 to 1 depending on the smoothness of the tumor region. Solidity of smooth regions is close to 1 and solidity of patchy regions is close to 0. In order to get the convex area, first a binary image must be obtained using the B-scan image. In our case, binary image is the tumor region. In the first step, boundary of the tumor region is detected point by point; in the second step, data points forming the boundary are converted to a closed

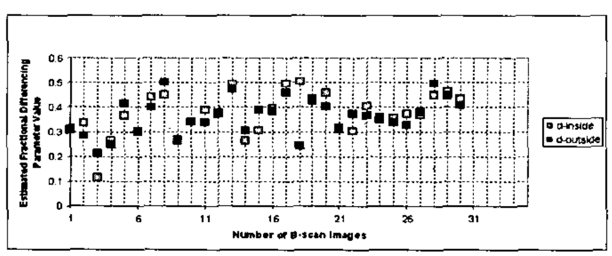

Fig. 1. Mean value of fractional differencing parameter d for inside and outside the tumor region for randomly selected 30 patients.

region boundary, and in the final step, all the tumor region is filled.

After obtaining the binary image, we determine the convex area using binary image functions of MATLAB, which measures the properties of the image like area, centroid, orientation, extrama, etc. The steps for obtaining the area of the tumor region and the convex area of the tumor region are shown in Fig. 2(a), 2(b), 2(c), 2(d), respectively.

As for the second sonographic feature, number of corners related to the margin properties is extracted for each B-scan image. Depending on the linearity of the margin, numbers of corners are expected to be larger in patchy regions compared to smooth regions. Sensitivity of the corner finding algorithm can affect the number of the corners estimated for each B scan image. Taking this into account, in this work we used a standard sensitivity for the detection algorithm for all B-scan images.

The last sonographic feature is the depth to width ratio of the tumor region. If depth to width ratio is greater than 0.8 tumors are expected to be malignant. This feature can also be explained as a tumor being taller than wider on a B-scan image. If this is the case, tumor can be characterized as malignant. Radiologists can also observe this feature by looking at the B-scan image. In the same manner, if tumor is parallel to the skin it can be classified as benign. In our work, we calculated this feature in two steps. First we estimated the center of mass of the tumor region, then using this center of mass point we evaluate the depth to width ratio.

V. CLASSIFICATION FOR TISSUE CHARACTERIZATION

The features which are, F1 and F2 (mean and variance values of *d*), F3 (solidity), F4 (number of corners), F5 (depth to width ratio), F6 (patient age information) were used for classification purposes. The overall feature set was fused using a linear classifier (minimum least square linear classifier), a quadratic classifier (normal densities based quadratic classifier) and a nonlinear classifier (Parzen classifier) [10]. We used three techniques to monitor the bias, which are resubstitution, leave-one-out and hold-out methods. As expected, resubstitution method gave the best results since training and test sets are the same. Leave-one-out method, which is more realistic, gave better results than hold-out method which divides the total number of cases into two as training and test sets.

The ROC curves were obtained by plotting the probability of false alarm versus the probability of detection. Probability of detection is the ratio between the number of correct malignant decisions and total number of malignant cases (45). The probability of false alarm is the ratio between the number of incorrect benign decisions and total number of benign cases (75). The 95% confidence interval for the area under the ROC curves was obtained using

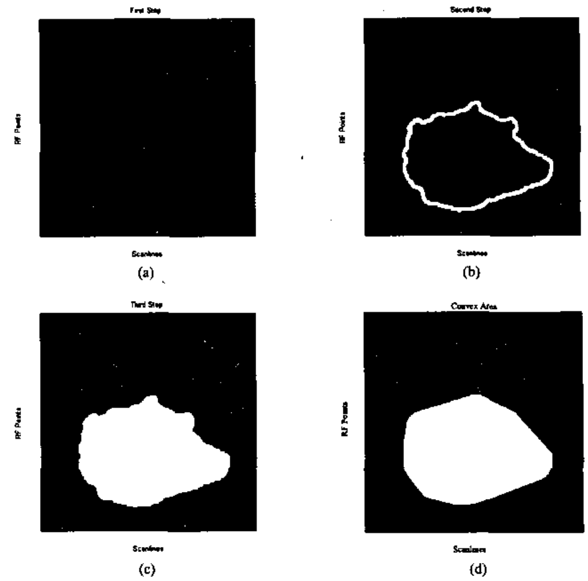

Fig. 2. Steps for obtaining convex area of a tumor region

bootstrap procedure and all three methods (resubstitution, leave-one-out, hold-out) were used in the procedure.

In Fig. 3, ROC curves for individual features are given. The observed area ranges from 0.6243 to 0.7973 for 6 different features. The best feature is the computer generated feature, which is the mean and variance of the fractional differencing parameter.

Tables I, II, III shows the overall performance of the combined features, again for each type of classifiers. The observed area is 0.894122 with a confidence interval of 0.02. Linear classifier gives better results in comparison with non-linear and quadratic classifiers.

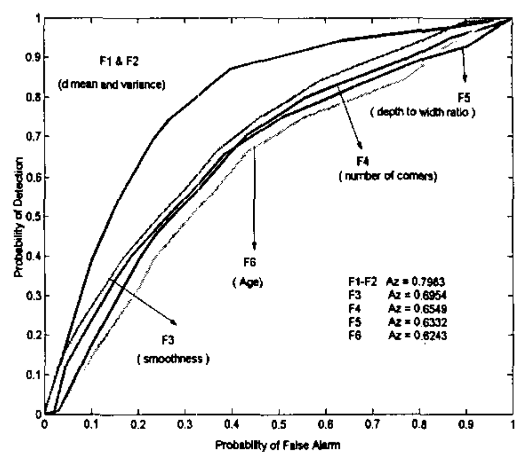

Fig. 3. ROC curves for individual features

TABLE I
Overall performance of combined features fused with linear classifier

	Linear	Linear	Linear
	Resubstitution	Leave-one-out	Hold-out
Az	0.92	0.89	0.83
Az+α	0.94	0.91	0.85
Az-β	0.90	0.87	0.81

TABLE II
Overall performance of combined features fused with quadratic classifier

	Quadratic	Quadratic	Quadratic
	Resubstitution	Leave-one-out	Hold-out
Az	0.90	0.85	0.80
Az+α	0.91	0.87	0.83
Az-β	0.87	0.79	0.76

TABLE III
Overall performance of combined features fused with Parzen classifier

	Non-linear	Non-linear	Non-linear
	Resubstitution	Leave-one-out	Hold-out
Az	0.89	0.83	0.79
Az+α	0.91	0.85	0.81
Az-β	0.85	0.81	0.77

In Fig. 4, ROC curves for different combinations of features are given. The best classification outcome results when all six of the features were used. As seen from the results, even when the patient age information is not used, the area under the ROC curve is 0.8371.

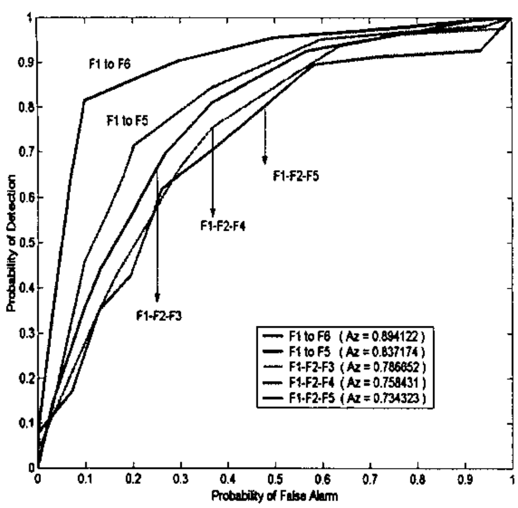

Fig. 4. ROC curves for different combinations of features.

VI. CONCLUSION

In this paper, we aimed to show that features obtained by statistical modeling of RF echo, together with the features obtained by using the morphology of tumor regions, can be used as a decision criterion for tissue characterization. A database of B-scan images was used to generate the features, which were all fused using different types of classifiers. The area under the ROC curve is 0.8941 with a 95% confidence interval, showing that the proposed method can potentially be used to the decrease number of unnecessary biopsies performed on benign masses. In spite of the limited size of the population, small estimation or data acquisition errors, our study shows that computer generated features can be used as an alternative opinion for radiologists. As a future work, as well as increasing the number of B-scan images and sonographic features, we are planning to design a software interface that will give an opinion about the characteristics of a B-scan image. This interface will be using a database which has all the previous B-scan images and features extracted from these images.

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