Breast Cancer Diagnosis Based on Ultrasound RF Echo Modeling and Physician's Level of Confidence

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Abstract— A number of researchers have shown that the ultrasound RF echo from tissue exhibits $(1/f)^{\beta}$ characteristics and developed tissue characterization methods based on the fractal parameter of the received signal. In this paper a new model for the received ultrasound RF data has been proposed, namely the Fractional Differencing Auto Regressive Moving-average (FARMA) model, whose parameters were investigated for their ability to differentiate between benign and malignant tumors. Along with the FARMA model parameters, the patient's age and the radiologist's pre-biopsy level of suspicion (LOS) were used as additional features to increase the characterization performance. 120 *in vivo* B-scan images obtained from 90 patients were used during the modeling and estimation procedures. The area under the receiver operator characteristics (ROC) curve yields a value of 0.87, with a confidence interval of [0.85, 0.89], at a significance level of 0.05. These results indicate that the proposed tissue characterization method can be used as a second opinion to aid the radiologist decision criteria.

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

I. INTRODUCTION

Many studies point out that high-quality ultrasound characterization imaging methods can aid radiologists to differentiate with greater degree of confidence between benign and malignant tumors detected by mammography [1], [2]. To improve the usefulness of ultrasound methods 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 the number, spacing or type of scatterers can be the identifiers of the tumor types in breast [3], [4].

In this paper we model ultrasound RF echo as a Fractional Differencing Auto-regressive Moving-average (FARMA) process to capture the speckle texture. Transducer response is modeled as an ARMA process, and tissue response is modeled as a fractional differencing process (FDM), leading to a FARMA process for the RF echo.

Transducer response, i.e., ARMA parameters, are estimated using phantom data, based on the final prediction error (FDE) and residual time series methods. Next, the transducer response is deconvolved from the RF echo and the mean and variance of FD parameter d is estimated from the resulting signal, based on a log periodogram technique.

A feature vector composed of the mean and variance of the fractional differencing parameter d, patient age and radiologist's pre-biopsy level of suspicion (LOS) is formed. Classification of the vector based features is achieved using three different classifiers and three different techniques. Finally, the receiver operator characteristics (ROC) for the proposed method is derived using 120 in vivo ultrasound breast images containing both benign and malignant tumors. The resulting ROC has an area of 0.89, shows that the proposed method can be used effectively to differentiate between benign and malignant breast tumors.

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 give classification techniques and performance evaluations of these techniques. Finally, remarks and future directions are provided in Section V.

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 tissue response.

It was empirically observed by Petropulu *et. al* [4] and Onaral *et. al* [5] that the tissue response exhibits *1/f* characteristics due to the complex structure of tissue scatterers. Fig. 1 illustrates the power spectral density of the envelope of RF echo data for two different estimation techniques taken from inside the tumor region. In addition to power spectral estimates, log-log estimate of PSD is also displayed in this figure.

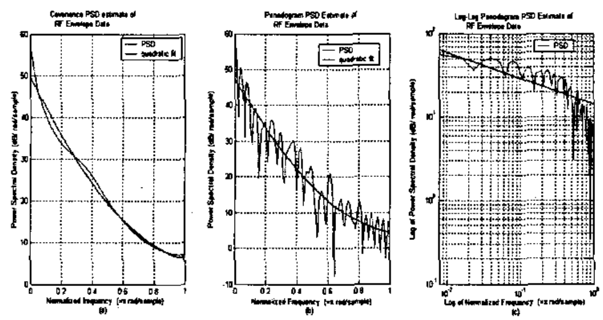

Fig. 1. The power spectral density of envelope of RF echo with two different estimation methods, (a) PSD with covariance method, (b) Periodogram of the envelope of RF echo, (c) log-log periodogram of envelope of RF echo.

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, $0<d<0.5$.

Fractional differencing 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 squares 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 breast 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 in 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. 2, we present the mean values of the parameter *d* obtained from inside and outside the suspected tumor for randomly selected 30 patients.

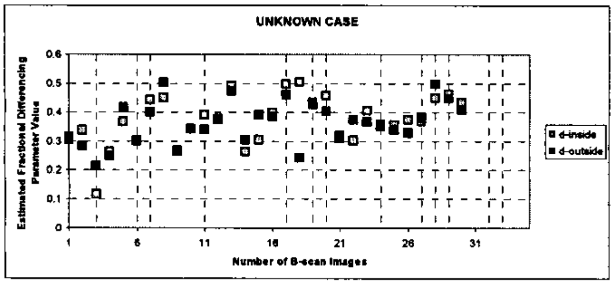

Fig. 4. Mean value of fractional differencing parameter *d* for inside and outside the tumor region for randomly selected 30 patients.

IV. CLASSIFICATION FOR TISSUE CHARACTERIZATION

The features which are, F1 and F2 (mean and variance values of *d*), F3 (LOS), F4 (patient age information) were used for classification purposes. The overall feature set was fused using a linear classifier (minimum least squares 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 malignant decisions and total number of benign cases (75). The 95% confidence interval for the area under the ROC curves was obtained using bootstrap procedure for all three methods (Resubstitution, leave-one-out, and hold-out methods) were used in the procedure.

In Fig. 5, ROC curves for individual features are given. The observed area ranges from 0.65 to 0.79 for 4 different features. The best feature set is the combination of the computer generated features, which are the mean and variance of the fractional differencing parameter *d*.

Tables I, II, III show the overall performance of the combined features for each type of classifier and include the Az for the experimental data and its 95% confidence interval. When a linear classifier is used together with the resubstitution method, the area under the ROC curve for the observed region is 0.87 with a confidence interval of around 0.02. This is the best scenario for the overall classification performance. As seen from Tables I, II, III, linear classifier yields better results in comparison with the

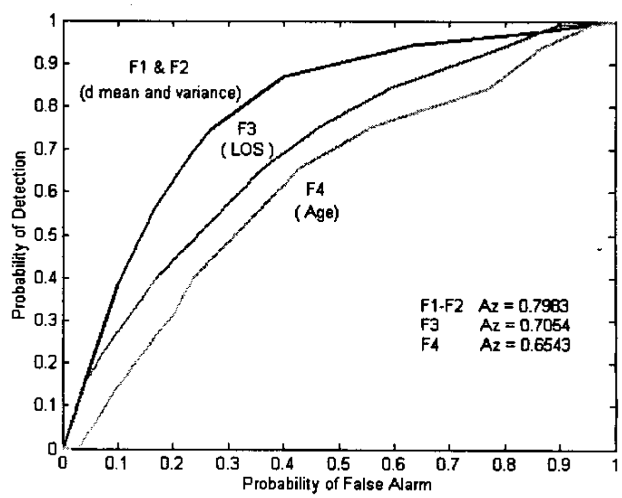

Fig. 5. ROC curves for individual features

TABLE I
Overall performance of combined features fused with linear classifier

	Linear	Linear	Linear
	Resubstitution	Leave-one-out	Hold-out
Az	0.87	0.84	0.80
Az+α	0.89	0.86	0.83
Az-β	0.85	0.82	0.79

TABLE II
Overall performance of combined features fused with quadratic classifier

	Quadratic	Quadratic	Quadratic
	Resubstitution	Leave-one-out	Hold-out
Az	0.85	0.82	0.77
Az+α	0.86	0.84	0.80
Az-β	0.82	0.79	0.75

TABLE III
Overall performance of combined features fused with quadratic classifier

	Non-linear Resubstitution	Non-linear Leave-one-out	Non-linear Hold-out
Az	0.84	0.81	0.76
Az+α	0.86	0.83	0.78
Az-β	0.83	0.80	0.75

non-linear and quadratic classifiers for all three methods.

In Fig. 6, ROC curve for the complete feature set is given. The best classification results were obtained when all four features were used. Addition of features F3 and F4 to the complete feature set increased the overall performance of the classification results. The area under the ROC curve obtained for the mean and the variance of the fractional differencing parameter *d* enhanced from 0.79 to 0.89 which is a considerable increase.

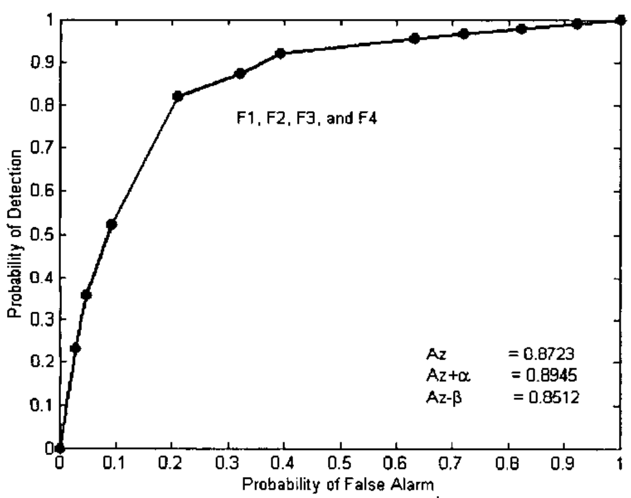

Fig. 6. ROC curve for the complete feature set, which are mean and variance of fractional differencing parameter (F1 and F2), radiologist's pre-biopsy level of suspicion (F3), and patient age (F4).

VI. CONCLUSION

In this paper, we demonstrated that features obtained by statistical modeling of RF echo 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 resulting area under the ROC curve is 0.89 with a 95% confidence interval, showing that the proposed method can potentially be used to decrease the number of unnecessary biopsies performed on benign masses. In spite of the limited size of the population, and the corresponding estimation or data acquisition errors, our study shows that computer generated features can be used as an alternative opinion for radiologists. In future work, a software interface will be designed to yield computerized decision levels about the characteristics of the lesions obtained from the B-scan breast images. This interface will use a database that contains all the previous B-scan images and the features extracted from these images.

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