A WOLD DECOMPOSITION BASED AUTONOMOUS SYSTEM FOR DETECTING LESIONS IN ULTRASOUND IMAGES OF THE BREAST.

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ABSTRACT

This paper presents a multiparameter tissue characterization system based on the features obtained from the Wold decomposition algorithm when applied on real breast images. The Wold decomposition features quantify parameters of the tissue structure. This model was applied to a large database of real ultrasound images of the breast. The features obtained were used to classify tissue pathology. To design properly the multi-parameter classifier we take under consideration issues such as the dimensionality of the feature vector and the partition of the data set into training and test data.

1. INTRODUCTION

The motivation of this study is to design an autonomous multi-parameter tissue characterization system. The available features are obtained by applying the Wold decomposition algorithm on preselected regions of ultrasound images of the breast. Insana et. al. in 1986 [2] used pattern recognition techniques to differentiate between normal liver and chronic active hepatitis using four ultrasonic parameters. They assumed the data to be normally distributed and used principal component analysis as well as quadratic and linear discriminant functions to reduce the feature vector's dimensionality. Garra et. al. in 1989 [3] used the linear Bayes classifier to separate of healthy versus chronic hepatitis cases as well as healthy versus Gaucher's disease cases. Garra et. al. in 1993 [4] used fractal analysis and statistical texture analysis to distinguish benign from malignant breast lesions with very good results.

2. WOLD DECOMPOSITION

The Wold decomposition is a parametric model for ultrasound radio-frequency (RF) data that models the data as a superposition of a deterministic and a random part. The deterministic part (if it exists) is described by a periodic sequence of period $m$. The random part is described by an AR process of low order. The features produced by the algorithm are the residual error variance, the AR parameters, the period $m$ and the Fourier coefficients of the coherent part. All these features describe quantitatively the tissue structure. The database of available images contained 187 B-scan images from 47 patients, obtained in the Radiology department of the Thomas Jefferson Hospital. This database contains multiple scans of the same patient. The pathologies of interest are as follows: 14 carcinoma cases, 23 fibroadenoma cases and 10 fibrocystic and stromal fibrosis cases. Two regions of interest (ROI's) were selected on each image, one ROI on the lesion and one ROI away from the lesion. Because there are multiple scans per patient, we have 53 carcinoma ROI's, 101 fibroadenoma ROI's and 33 fibrocystic and stromal fibrosis ROI's. The desirable multi-parameter classifier needs to be designed by using the above mentioned parameters.

3. CLASSIFIER METHODOLOGY AND CONSIDERATIONS.

We use Fisher's linear discriminant function [5] to reduce the dimensionality of the 1-dimensional feature vector. Assume that we have a set of $N_i$ ($i = 1, 2$) 1-dimensional features $x_1, \ldots, x_{N_i}, N_1$ features in class $\omega_1$ and $N_2$ features in class $\omega_2$. The Fisher's linear discriminant is defined as:

$$w = S^{-1}_w (\mu_1 - \mu_2), \quad \mu_i = \frac{1}{N_i} \sum_{x \in \omega_i} x$$

where $\mu_1, \mu_2$ are the sample means and $S_w$ is the within-class scatter matrix:

$$S_w = S_1 + S_2, \quad S_i = \sum_{x \in \omega_i} (x - \mu_i)(x - \mu_i)'$$

The 1-dimensional feature vector produced by using $w$ is:

$$y = w'x$$

When $l > N$ the matrix $S_w$ is singular because it is a sum of $N$ independent $l$ by $l$ matrices of rank one [5]. In this case we use the diagonal elements of $S_w$ in other words we treat the features as uncorrelated features even if there is significant correlation. The problem of dimensionality was analytically discussed by Foley in [6]. To overcome the dimensionality problem in this paper we use a small number of features (six features at most). The performance of the classifier is shown using the empirical Receiver Operating Characteristics (ROC) technique. The use of the same set of data for the design and the performance evaluation of the classifier will give a biased estimate of the performance. To overcome this problem we can partition the data set into a training set and a test set. In this study we have chosen...
larger number of features, that the area under the ROC curves is higher when using a five AR parameters and is presented in Fig. 2. We notice analysis was applied to the residud error variance and the carcinoma tissue parameter is displayed. We notice that between diseased and normal tissue, but they are weak when the Weld decomposition features strongly discriminate between fibrocystic and stromal fibrosis versus carcinoma tissue parameter. Fig. 1(f) fibroadenoma versus versus benign tissue parameters. In Fig. 1(e), the ROC parameter. On the last row we present ROC'S of malignant fibrocystic and stromal fibrosis tissue parameter. Fig. 1(d) presents the ROC of normal versus fibroadenoma tissue parameter. On the last row we present ROC's of malignant versus benign tissue parameters. In Fig. 1(c), the ROC of fibrocystic and stromal fibrosis versus carcinoma tissue parameter is displayed, while on 1(f) fibroadenoma versus carcinoma tissue parameter is displayed. We notice that the Weld decomposition features strongly discriminate between diseased and normal tissue, but they are weak when used to discriminate different kinds of pathology. The same analysis was applied to the residual error variance and the five AR parameters and is presented in Fig. 2. We notice that the area under the ROC curves is higher when using a larger number of features.

5. CONCLUSIONS

In this paper we used the features obtained from the Weld decomposition algorithm when applied on real ultrasound images of the breast to design a multi-parameter classifier for diagnostic purposes, i.e., to classify a given ROI as normal benign or malignant. The Weld decomposition features are a novel set of features for the ultrasound data and are very closely related to the tissue microstructure. They proved to be very effective when used to discriminate between normal pathologic tissue but are weak when used to classify between different pathologies of the tissue.

4. RESULTS ON BREAST DATA

The pathologies of the patients as well as the number of ROI's obtained from each pathology were presented in section 2. The estimated parameters of the model from all ROI's were recorded and empirical ROC techniques were used to evaluate the detection rate of the Weld decomposition on breast images using single parameters. ROC analysis showed that the two strongest single parameters are the residual error variance and the second AR parameter. Using these two parameters, the Fisher discriminant analysis and the "round robin" technique we produced six empirical ROC curves (Fig. 1). In 1(a), the ROC of normal versus diseased tissue parameter is displayed. In Fig. 1(b) the ROC of normal versus carcinoma tissue parameter is displayed. In Fig. 1(c), we show the ROC of normal versus fibrocystic and stromal fibrosis tissue parameter. Fig. 1(d) presents the ROC of normal versus fibroadenoma tissue parameter. On the last row we present ROC's of malignant versus benign tissue parameters. In Fig. 1(e), the ROC of fibrocystic and stromal fibrosis versus carcinoma tissue parameter is displayed, while on 1(f) fibroadenoma versus carcinoma tissue parameter is displayed. We notice that the Weld decomposition features strongly discriminate between diseased and normal tissue, but they are weak when used to discriminate different kinds of pathology. The same analysis was applied to the residual error variance and the five AR parameters and is presented in Fig. 2. We notice that the area under the ROC curves is higher when using a larger number of features.

6. REFERENCES