ULTRASONIC TISSUE CHARACTERIZATION FOR THE CLASSIFICATION OF PROSTATE TISSUE

U. Scheipers[1], K. König[2], H.-J. Sommerfeld[2],
M. Garcia-Schürmann[2], T. Senge[2], S. Philippou[3], and H. Ermert[1]

[1] Lehrstuhl für Hochfrequenztechnik, Ruhr-Universität Bochum (RUB), Germany
[2] Urologische Universitätsklinik der RUB, Marienhospital Herne, Germany
[3] Institut für Pathologie, Augusta-Krankenanstalt Bochum, Germany
[1, 2, 3] KMR – Kompetenzzentrum Medizintechnik Ruhr, Bochum, Germany
ulrich.scheipers@rub.de

Abstract

The incidence of prostate carcinoma is one of the highest cancer risks in men in the western world. Its position in cancer mortality statistics is also among the highest. The conventional types of diagnostics that are used today lack reliability and are therefore not sufficient when it comes to early detection of prostate cancer.

Diagnosis of prostate carcinoma using multi-feature tissue characterization in combination with ultrasound allows the detection of tumors at an early stage and thus can aid the conducting physician in finding a diagnosis.

Spatially resolved parameters and contextual information extracted from radio frequency ultrasound data are used for the classification. Nonlinear classification is done by an adaptive neuro fuzzy inference system. Next to hypo- and hyperechoic tumors, also isoechoic tumors can be visualized.

Volume reconstructions of malignant regions within the prostate capsule might improve biopsy guidance and therapy planning. Volume renderings might also improve disease staging.

Introduction

Successful treatment of prostate cancer is only possible if tumors are diagnosed at an early stage. The recurrence rate of prostate cancer treated at later stages is high. The different types of diagnostics that are used today (digital rectal examination, transrectal ultrasound and PSA value analysis) lack reliability, even if used in combination, and are therefore not sufficient. Results of diagnostics using conventional B-mode ultrasound are highly dependent on the physician's skills. Digital rectal examination might easily miss smaller tumors at deeper positions within the prostate. PSA values are dependent on several factors that are hard to comprise into diagnostics. Real-time strain imaging has not found wide acceptance yet and is so far only applied in certain clinics.

Diagnosis of the prostate carcinoma using ultrasonic tissue characterization allows the detection of tumors at an early stage. Using adaptive neuro-fuzzy inference systems as nonlinear classifiers can automate the process of finding prostate cancer and can therefore help closing the gap between different results of diagnostics between sophisticated and novice physicians using ultrasound as a diagnostic modality.

Methods

In the underlying system, radio-frequency ultrasonic echo data of the prostate is captured during the usual examination of the patient with standard ultrasound equipment (Kretz Combison 330, 7.5 MHz transrectal transducer). After amplification by a custom made hardware TGC (time gain control) the data is directly transmitted to a PC by ADC at 33 MHz and subdivided into up to 1000 regions of interest (ROI) per prostate slice to yield spatially distributed classification results. The size of the ROIs used in this approach is 128 sample points at 16 lines with 75 % and 50 % overlap, respectively. The data is compensated for TGC amplification and for system induced effects using point spread functions measured at different depths.

Several parameters describing the histological characteristics of the underlying tissue are calculated for each ROI and fed into two adaptive network-based fuzzy inference systems working in parallel. One system is used to classify hypo- and hyperechoic tumors, the other system is used to find isoechoic tumors within the normal prostate tissue.

The systems are trained by using subtractive clustering as the first step followed by a backpropagation algorithm. Following morphological analysis combines clusters to mark areas of similar tissue characteristics. It was found that the fuzzy inference systems underestimate the malignant areas, so morphological post processing is used to compensate the effects of underestimation. Morphological post processing is performed by two dimensional filtering of the output of the two fuzzy inference systems by previously determined filter kernels and cut off thresholds.

The results of the two fuzzy inference systems are combined to build a malignancy map, which consists of a conventional B-mode ultrasound image in which areas of high cancer probability are marked in red.

The malignancy map can be presented to the physician during the examination on a PC screen. Volume renderings of the prostate can be calculated off-line for further diagnostics, setting up needle biopsies and therapy planning.

Fourier based Spectrum parameters

Spectrum parameters are calculated after applying a Hamming window to the TGC-compensated RF data of each ROI, computing the Fourier transform (FT) and converting the resultant power spectrum to dB. Spectral results of each scan line are averaged to form an estimate of the average power spectrum [1].

The primary set of spectrum parameters consists of four measures of backscatter calculated for the signal bandwidth. The parameters used in this approach are: slope, axis intercept, midband value, and square deviation of the linear regression spectrum fit [2, 3, 4, 5, 6, 7]. The measures of backscatter are compensated for attenuation effects using an attenuation model, which is based on the multi narrow band method [8, 9, 10]. Three measures of this attenuation model are also included in the system [4, 6]. The attenuation parameters used in this approach are: slope, axis intercept and midband value. It has been shown earlier by Thijssen et al. [1] and Oosterveld et al. [9] that it is important for the calculation of attenuation parameters to exclude all ROIs with overflows, underflows or severe inhomogeneities. ROIs containing these properties are being discarded before calculation. Statistical frameworks for ultrasonic spectral parameter imaging have been proposed by Huisman et al. [11] and Lizzi et al. [12].

Auto Regression based Spectrum Parameters

If the spatial resolution of the malignancy maps plays an important role, as it does in this approach, because the goal is finding even small lesions within the prostate, there is a discrepancy between the accuracy of the feature estimations and the underlying size of the ROIs. On one side, as much data as possible is needed for an accurate parameter estimation, which demands large-size ROIs, on the other side, the resolution of the malignancy maps is wanted to be as high as possible to achieve fine resolved tumor areas and to keep the detectable lesion size as small as possible.

It has been shown earlier, that the extraction of features based on the backscattered echo signal is a valuable tool for discriminating different tissue types [3-6]. In most cases this feature extraction is based on conventional Fourier transform to convert the underlying echo signals into the frequency domain and to calculate the power spectrum from which the features are extracted.

When using Fourier transform, the underlying time series have to be windowed to cope with spectral leakage, which may occur when a rectangular window is used for sliding window technique. A typical window that is often used in this background is the Hamming window. During the windowing process, a certain amount of information is lost, due to the masking effect of the window. Because of this loss of information, it is advantageous to use techniques that bypass the windowing process. The most popular of these techniques that is used in the field of tissue characterization is the autoregressive (AR) analysis or system identification [13].

Next to auto regression parameters the order of the autoregressive process has to be determined. When both, the auto regression parameters and the order of the underlying process have to be determined, the task is called 'system identification'. Some methods have been proposed to determine the order minimally needed to model the process sufficiently well. The straightforward method is to calculate the auto regression parameters for several orders and to compare the resultant impulse response with the original time series using an error measure like the mean square error (MSE) and deciding which MSE can be tolerated for the problem. Next to this straightforward approach, other analytical methods like the Akaike information criterion (AIC), the minimum description length (MDL) and the final prediction error (FPE) have been proposed to estimate the optimal order of the auto regressive process. All four methods have been applied on the underlying data in order to estimate the optimal order of the autoregressive process. The four estimates are visualized for different model orders in the following figures.
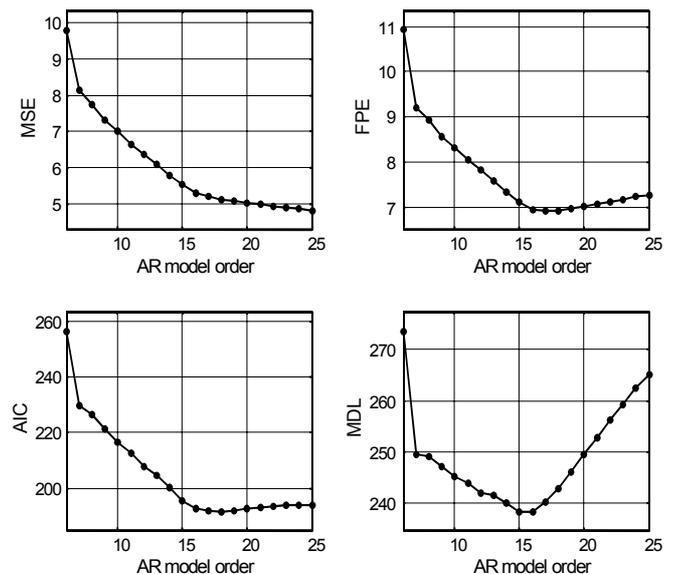

Figure 1: Four different methods for minimum order determination of AR models: mean square error (MSE), final prediction error (FPE), Akaike information criterion (AIC), and minimum description length (MDL). Minima are found between 15 and 18 depending on the method.

It is apparent, that both AIC and FPE lead to similar results, while MDL tends to give a slightly lower rate as model order estimate. The MSE is not easy to read, as the curve keeps on decreasing and no clear plateau is reached in this example. According to the estimations, a model order of 15 was chosen for the following calculations.

Four auto regressive spectral parameters were calculated from the spectrum and from the linear regression spectrum fit: slope, intercept, mid band value and square deviation of the spectrum fit.

The tissue characterization system described here is typically running on features extracted by Fourier transform [3-6]. For comparison with the conventional features, additional spectrum parameters were extracted by auto regressive models. Actually, auto-regressive parameters are used for window sizes smaller than the 128 samples used in this approach. Nevertheless the performance of AR parameters in comparison with the conventional FT parameters should be examined. As the overall system is too complex to easily change the window length to values lower than 128 sample points and as the applied attenuation estimation and correction is based on larger window sizes, only a length of 128 samples was used.

Results

During the clinical study, radio-frequency ultrasonic echo data of 100 patients were recorded. Prostate slices with histological diagnosis following radical prostatectomies are used as the reference. The ROC curve area is A=0.86 for hypo- and hyperechoic tumors and A=0.84 for isoechoic tumors using leave-one-out cross validation over patient datasets.

Next to spectrum parameters, texture parameters of first and second order and morphological features are used in this approach. The complete parameter extraction procedure and the nonlinear classification engine are described in detail in [3-6]. No autoregressive parameters were used in the final calculations. AR parameters are only stated here for comparison.

The results of the FT based parameters are displayed in Table 1. The performance of the AR based parameters is given in Table 2. For all parameters, the single classification results are given as the mean area under the ROC curve and its standard deviation for five fold cross validation over patients. Next to single classification results, the results of the fuzzy inference systems that have been trained on a combination of all four parameters are given. FIS 1 stands for the fuzzy inference system that was trained to distinguish between hypoechoic, hyperechoic tumors and normal tissue. The system that was trained to find isoechoic tumors within the prostate tissue is called FIS 2.

Table 1: FT based spectrum parameter results

FT-Parameters	FIS 1		FIS 2	
	A_Z	σ	A_Z	σ
Axis intercept	0.590	0.014	0.550	0.014
Slope	0.558	0.007	0.510	0.014
Mid band value	0.622	0.015	0.558	0.032
Square deviation	0.512	0.001	0.500	0.006
Combination	0.658	0.005	0.574	0.027

It can be seen, that the FT based parameters perform slightly better for hyper- and hypoechoic tumors, when only considering the mean value of the five fold cross validation results. For FIS 1 the standard deviation of the AR based parameters is about ten times larger than the standard deviation of the FT based parameters. Consequently, the use of FT parameters should be preferred. Taking a look at FIS 2, it is apparent, that both the mean classification rate and the standard deviation perform better for the AR based parameters, though the differences are only minimal. Interesting to know, the square deviation of FIS 1 is the same for both approaches, FT and AR. This indirectly proves the correct choice of model order, at least for FIS 1, though the standard deviation between the two approaches is different and the results of FIS 2 are slightly different as well.

Table 2: AR based spectrum parameter results

AR-Parameter	FIS 1		FIS 2	
	A_Z	σ	A_Z	σ
Axis intercept	0.583	0.028	0.567	0.034
Slope	0.592	0.046	0.550	0.060
Mid band value	0.626	0.025	0.564	0.035
Square deviation	0.512	0.016	0.527	0.015
Combination	0.642	0.049	0.577	0.020

The following figures show typical volume reconstructions of malignant areas within the prostate capsule. The whole organ is shown yellow while areas of a high cancer probability are colored red. The volumes are reconstructed using two dimensional datasets, which were recorded at defined positions within the prostate. The volumes shown here were reconstructed from 15 data slices.
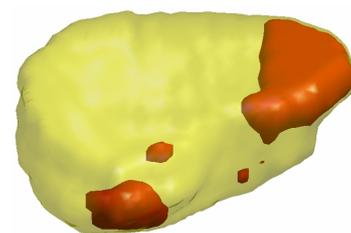

Figure 2: Typical volume reconstruction of tumor within prostate capsule at variable angles.

The volume renderings can aid in the planning of needle biopsies. Reduced amounts of needle cores and improved placing might be possible. Next to needle biopsies, the volumetric presentation can help planning therapies, like Brachy therapy, thermo therapy and HIFU therapy (high intensity focused ultrasound), which aim at local malignant areas and not at the whole organ like conventional prostatectomy. For local therapies, the exact position and border of the tumors are necessary. This information is made available by multifeature tissue characterization.

Figure 3: Typical volume reconstruction of tumor within prostate capsule at variable angles.

Conclusion

Classification results of A_Z=0.86 for hypo- and hyperechoic tumors and A_Z=0.84 for isoechoic tumors using leave-one-out cross validation over patient datasets prove the ability of the described system to improve the early detection of prostate cancer.

Biopsy and therapy planning can be improved. By using volume reconstructions of malignant regions within the prostate capsule even the staging of the disease might be improved.

It was shown that the use of auto regressive models instead of conventional Fourier transform cannot significantly improve the classification rates when classifying the underlying prostate tissue and using time series or window lengths of 128 sample points.

Acknowledgments

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