ULTRASONIC MULTIFEATURE TISSUE CHARACTERIZATION FOR THE EARLY DETECTION OF PROSTATE CANCER

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Abstract – The incidence of the 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 prostate carcinoma is only curable at an early stage. Therefore, early detection is extremely important. At an early stage the prostate carcinoma is limited to the prostate capsule and can hence be cured performing radical prostatectomy.

The different types of diagnostics that are used today (digital rectal examination, transrectal ultrasound and PSA value analysis) lack reliability and are therefore not sufficient. Even a combination of these three methods is not sufficiently reliable.

Diagnosis of the prostate carcinoma using multifeature tissue characterization in combination with ultrasound allows the detection of tumors at an early stage. Also biopsy guidance and planning can be improved. This results in reduced costs for cancer treatment.

I. METHODS

Data Acquisition

Radio-frequency (RF) ultrasonic echo data of the prostate is captured during the usual examination of the patient with standard ultrasound equipment (Kretz Combison 330, transrectal probe, 7.5 MHz center frequency). Patient compliance is high, as the new method does not extend the normal examination time when applying transrectal ultrasound and the system is operator-independent. The RF-data is directly transmitted to a PC, sampled at 33 MHz and 12 bits and subdivided into up to 1000 segments per prostate slice. Up to five datasets per patient are being recorded.

Parameter Extraction

Up to 40 parameters are calculated for each segment. The extracted parameters do not claim to be independent of the ultrasound equipment. The parameters used for classification are calculated from the frequency spectrum and from the time domain. Spectrum parameters are calculated after applying a Hamming window to the RF data, computing the Fourier transform and converting the resultant power spectrum to dB. The primary set of spectrum parameters consists of measures of backscatter calculated for the signal bandwidth (slope, axis intercept, midband value, integrated power and deviation of the linear regression spectrum fit [1][3][5]). Parameters of an attenuation model (multi narrow band method [2][7][8]) are also included in the system.

The texture parameters consist of first and second order (Cooccurrence) parameters. Common co-occurrence parameters are calculated for different distances [3][6].

Initial results have shown that only a combination of these different fields of descriptors leads to adequate classification results. During the pre-selection procedure of parameters for the training process of the system, parameter vectors that are highly dependent on each other are found and discarded using covariance matrix analysis. Parameter vectors that have a small influence on the classification procedure are found and discarded using single classification. During the preselection the number of parameters is reduced from 40 to 16 for both fuzzy inference systems. As the number of segments used in this work is very high, using up to

16 parameters for the classification procedure is a safe approach [9].

System Description

Two fuzzy inference systems (FIS) working in parallel classify and separate the segments into two classes (negative = benign, positive = malign). The fuzzy inference systems used in this work are based on Sugeno type systems with up to six gaussian membership functions per input parameter. The number of required membership functions is chosen adaptively by the system.

The fuzzy output maps of the two fuzzy inference systems are transformed into binary 1/0-maps applying a threshold to divide the two classes. The threshold can be chosen freely by the operator as the implemented system is a quantitative system.

A following morphological analysis combines clusters in the binary output maps of the fuzzy inference systems to mark areas of similar tissue characteristics. The clustering procedure is implemented by two dimensionally filtering the binary output maps with symmetric 1/0-kernels of empirically determined size. This step improves the classification rate by a non-significant amount but makes the malignancy maps more readable by the physician. Applying 'opening' and 'closing' filters has been evaluated but found worthless.

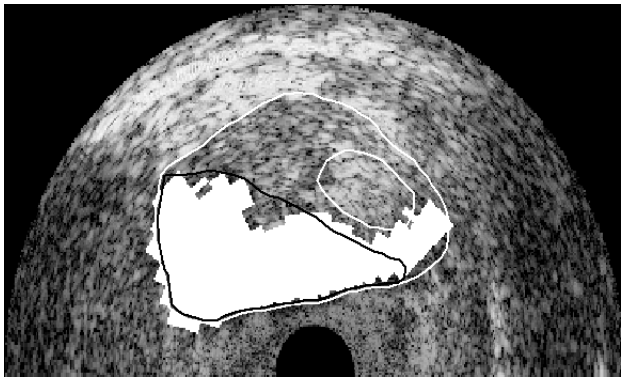

Figure 1: Overlay of B-mode image and malignancy map. Areas of a high cancer probability are marked white.

The results of the two fuzzy inference systems are combined to build a malignancy map, which consists of a traditional B-mode image in which areas of a high cancer probability are marked in red (white on printed matter). The malignancy map (Figure 1) is presented to the physician during the examination on a PC screen and thus can supplement the existing methods of diagnostics. Malignancy maps can easily be printed or archived for biopsy planning.

II. CLINICAL STUDY

During a clinical study, radio-frequency ultrasonic echo data of 100 patients undergoing clinical examinations have been recorded. Prostate slices with histological diagnosis following radical prostatectomies act as the gold standard. The RF datasets have been divided as described above resulting in 130,000 benign and 40,000 malign segments.

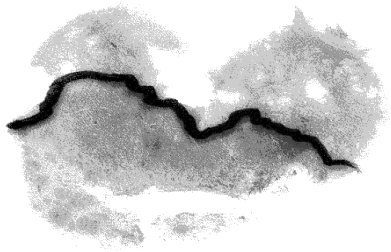

Figure 2: Histology, tumors have been stained, malign and benign tissue areas have been marked by pathologist

Cancerous areas have been stained and marked on the prostate slices. Malign areas have been encircled by the pathologists (Figure 2). The contours have been transferred to the PC by experienced physicians thus making a definite assignment of dataset segments to tissue classes possible (Figure 3).

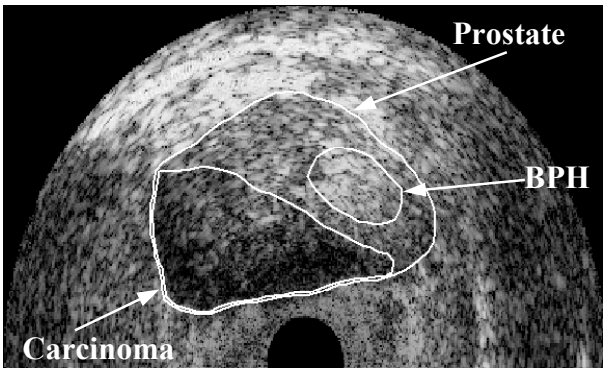

Figure 3: B-mode image with contours.

For classification reasons the tumors have been divided into two different classes. The first class (PS)

consists of all tumors that were visible in the classical B-mode image. Isoechoic tumors have as well been included in this class as hyperechoic tumors. The second class (PU) consists of all tumors that were not visible in the classical B-mode. That means this tumors appear in the B-mode image in the same manner than healthy tissue. Prior work has shown that the partitioning of the entire amount of malign segments into these two classes improves the classification results quite significantly.

The third class (N) consists of all other kinds of tissue. Next to normal tissue segments also segments that consist of benign prostate hyperplasia belong to this class.

Successive two fuzzy inference systems have been trained. The first system was trained to distinguish the class PS from all other kinds of tissue (PU and N). The second system was used to distinguish between the class PU and all other kinds of tissue (PS and N).

III. RESULTS

Each of the two fuzzy inference systems yields a fuzzy value for each segment of the ultrasound dataset. The fuzzy value is a measure of the probability of a segment that consists of a defined tissue type to be malign or benign. The probabilities of a segment, to be malign or benign, when the segment has been classified into a certain range can be seen in figures 4 and 5. The two figures show the abilities of the two fuzzy inference systems to separate the classes.

As the classification procedure applied here represents a continuous system, sensitivities and specificities can be chosen freely under dependence of each other.

The ROC curve area is $A_1 = 0.83$ for the first system and $A_2 = 0.76$ for the second system respectively. The capability of the system has been determined using the leave-one-out classification method. Calculating sensitivities and specificities for the example point of sensitivity = specificity leads to a classification rate of 75 %.

Under the condition, that at least half of the histologically proven malign areas per patient could be identified as malign by the system and that at the same time the rate of false-positive classification is lower than 50 % per patient, 96 % of all patients could be classified correctly using the leave-one-out test.

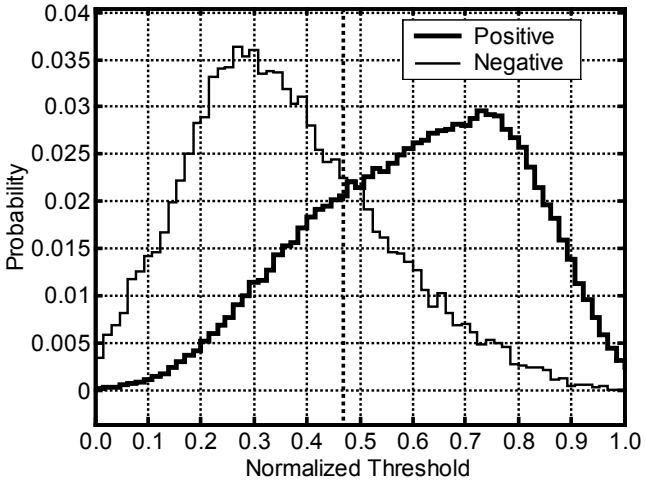

Figure 4: Probabilities plotted over normalized threshold for FIS 1 (PS against PU and N), ROC Curve area $A_1 = 0.83$.

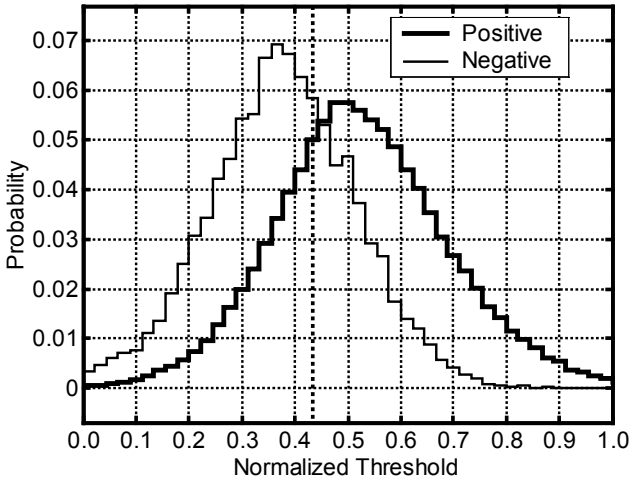

Figure 5: Probabilities plotted over normalized threshold for FIS 2 (PU against PS and N), ROC Curve area $A_2 = 0.76$.

IV. FUTURE WORK

Prior work has shown that the division of all malign segments into two classes PU and PS leads to better discrimination results. The class PS can still be divided into two sub-classes, one class existing of all tumors that appear as isoechoic areas in the B-mode image and one class existing of all tumors that appear as hyperechoic tumors. The subdivision of the class PS may lead to better discrimination results. As can

be seen in figure 4, the discrimination capabilities of FIS 1 are quite good. The constraint exists to improve the results of FIS 2. This may be possible using adaptive clustering to divide the class PU into subclasses. As the class PU consists of only 13,000 segments, a further subdivision may lead to subclasses that are too small to support a reliable training process.

V. Conclusion

It has been shown that our system for ultrasonic multifeature tissue characterization is able to detect the prostate carcinoma with a high grade of accuracy. Thereby the system can supplement the existing methods of prostate diagnostics to improve the early detection of prostate cancer and allow a more reliable diagnosis. The planning of biopsies can be improved, unnecessary biopsies can be avoided and performed biopsies can be guided more reliably.

VI. Acknowledgments

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VII. References

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