NEURO-FUZZY INFERENCE SYSTEM FOR ULTRASONIC MULTIFEATURE TISSUE CHARACTERIZATION FOR PROSTATE DIAGNOSTICS

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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 different types of diagnostics that are used today lack reliability and are therefore not sufficient.
Diagnosis of the 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 are used for the classification. Next to hypo- and hyperechoic tumors, also isoechoic tumors can be visualized.

I. METHODS

Data Acquisition

Radio-frequency ultrasonic echo data of the prostate is captured during the regular examination of the patient with standard ultrasound equipment (Kretz Combison 330/530, transrectal probe, 7.5 MHz center frequency). Patient compliance is high, as the new method does not extend the normal examination time. The system is operator-independent and easy to handle by the physician. The RF-data is directly transmitted to a PC after amplification by a custom made time-gain-control unit, sampled at 33 MHz and 12 bits with a PC-based ADC card (Gage Applied Inc.), compensated for diffraction and system dependent effects by deconvolution with the system's point spread function [9] and subdivided into up to 1000 ROIs per prostate slice. Five datasets per patient are being recorded.

Parameter Extraction

During the training phase, up to 40 parameters are calculated for each ROI. 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 logarithmizing the resultant power spectrum. At first, parameters of an attenuation model (multi narrow band method, [9, 6, 2]) are calculated after detection of over- and underflows of the ultrasonic echo data. The secondary set of spectrum parameters consists of measures of backscatter calculated for the signal bandwidth (slope, axis intercept, midband value, and deviation of the linear regression spectrum fit, [3, 5, 8]).

The texture parameters consist of first and second order (Cooccurrence) parameters. Common co-occurrence parameters are calculated for different distances [1, 7].

Under certain circumstances, some parameters used in this approach may lead to unreliable results. For example, attenuation measurements fail, if calculated behind calcifications. Some cooccurence parameters that are independent of the mean intensity still yield satisfying results under these circumstances. Because calcifications are, in most cases, found in the lower section of the prostate, this observation leads to the inclusion of morphological descriptors, that describe the position of the ROIs within the prostate, thus allowing the fuzzy inference system to choose different parameter combinations for different positions within the prostate tissue.

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. During the selection of parameters the number of parameters is reduced from 40 to 8 for both fuzzy inference systems. Five-fold cross-validation over patients is used during the selection of parameters. As the number of segments used in this work is very high, using up to 8 parameters for the classification procedure is a safe approach [4].

Information Model

The kinds of parameters described above have one property in common, which is the spatial independence of the ROIs from that the parameters are calculated to achieve spatially resolved parameter vectors or parameter maps. Considering an information model as shown in Figure 1, the whole information that is available about the patient and the prostate may be divided into three areas, that do, more or less, interfere with each other. Next to spatially resolved information in the form of spectral and textural parameters, so-called clinical information may be included into a classification system. Typical clinical variables are the PSA value and the volume of the prostate, but they may also include the age and race of the patient. Clinical variables are not spatially resolved and need a huge database to lead to reliable results.

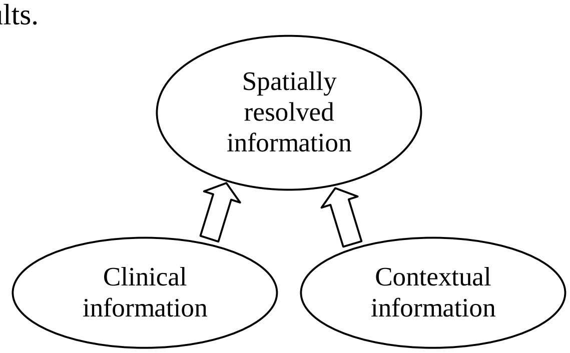

Figure 1: Information model for multifeature tissue characterization

The third part of the information model, named contextual information, which may also be called inter-segment dependence, is a new modality to the classification system described here. Contextual features contain information derived from ROIs surrounding the ROI being analyzed. Considering a ROI, which is surrounded by a certain amount of other ROIs of a certain class, the probability of the ROI being analyzed to belong to the same class as the majority of the surrounding ROIs is higher than the probability to belong to another class. Under this assumption, and when the gold standard is known, the size of the optimal and most significant neighborhood can be calculated.

Fuzzy Inference System

Two fuzzy inference systems working in parallel, one designed to find hypo- and hyperechoic tumors, the other intended to detect isoechoic tumors, classify and separate the segments into two classes (negative / positive). The fuzzy inference systems used in this work are based on Sugeno type systems with up to eight 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 inference systems are transformed into binary 1/0-maps applying a threshold to divide into two classes. The operator can choose the threshold freely.

Contextual information, which has so far been neglected in this field, is integrated into the system by following morphological analysis that combines clusters to mark areas of similar tissue characteristics. During this step, natural clusters, which are typical for tumors, are emphasized at the expense of resolution. The clustering procedure is implemented by 2D-filtering the binary output maps with symmetric 1/0-kernels of empirically determined size and by thresholding the resulting map at a determined threshold. This step improves the classification rate and makes the malignancy maps more readable for the physician. Applying ‘opening’ and ‘closing’ filters has been evaluated but found worthless.

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

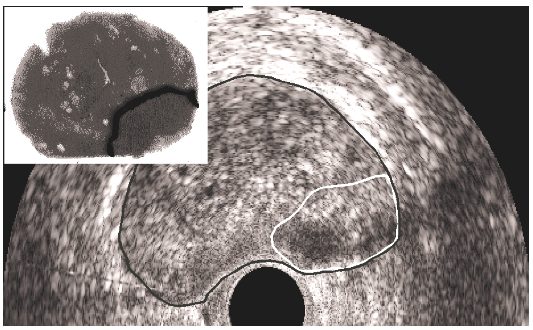

Figure 2: B-mode image with contours of prostate capsule and carcinoma as transferred from histology

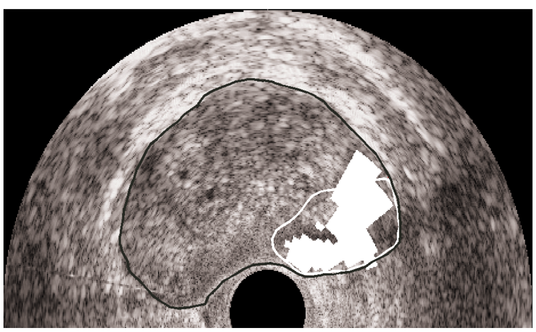

Figure 3: B-mode image with malignancy map as calculated by fuzzy inference system before post processing

Figure 4: B-mode image with malignancy map after post processing applying contextual information

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

For classification reasons the tumors have been divided into two different classes. The first class 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 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 as healthy tissue. Prior work has shown that the partitioning of the entire amount of malignant segments into these two classes improves the classification results quite significantly.

The third class 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 to distinguish between the two positive (malignant) classes and the negative (benign) class.

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 malignant or benign. 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_z=0.84 for isoechoic tumors and A_z=0.86 for hypo- and hyperechoic tumors, respectively, after post processing applying contextual information. Without post processing the ROC curve area is A_z=0.80 for isoechoic tumors and A_z=0.84 for hypo- and hyperechoic tumors, respectively. Typical malignancy maps are shown in Figure 3 and Figure 4. The improvement due to the morphological post processing can be seen comparing both figures.

The capability of the system has been determined using the leave-one-out classification method over patient data sets for cross-validation.

IV. FUTURE WORK

Prior work has shown that the division of all malignant segments into two classes (hypo- and hyperechoic tumors vs. isoechoic tumors) leads to better discrimination results. The first class of tumors can still be divided into two sub-classes, one class consisting of all tumors that appear as isoechoic areas in the B-mode image and one class consisting of all tumors that appear as hyperechoic regions. The subdivision of the first class may lead to better discrimination results.

V. CONCLUSION

It has been shown that the introduced system for ultrasonic multifeature tissue characterization for prostate diagnostics is able to detect the prostate carcinoma with a high degree of accuracy. ROC curve areas of $A_z=0.84$ for isoechoic tumors and $A_z=0.86$ for hypo- and hyperechoic tumors are achieved.

Morphological post processing applying contextual information improves the output of the fuzzy inference systems and ameliorates the presentation of the malignancy maps.

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 and brachytherapies 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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