Ultrasonic Tissue Characterization – Assessment of Prostate Tissue Malignancy *in vivo* using a conventional Classifier based Tissue Classification Approach and Elastographic Imaging

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Abstract - In this paper we present the development of a combined system which is able to exploit the benefits of two methods used for tissue characterization, strain imaging and tissue classification using a trainable classification system. Our system is able to acquire *in vivo* multi-compression rf-data for the calculation of the tissue strain, i.e. the elastic properties of tissue, induced by tissue compression. At the same time a Neuro-Fuzzy classification system is used to map the tissue malignancy. *In vivo* Classification results and *in vivo* strain images are presented. The images of the two new modalities are compared to demonstrate the advantages and restrictions of both methods.

INTRODUCTION

In the past, several ultrasound methods have been described to assess the malignancy of prostate tissue. Two major approaches are the investigation of tissue elasticity by strain imaging [1] and the detection of malignantant tissue areas by tissue classification with a trainable classification system [2].

Ultrasonic strain imaging refers to the visualization of tissue elasticity for medical diagnosis. With this technique small displacements between ultrasonic image pairs which are acquired under varying axial compression are determined using a cross-correlation analysis of corresponding a-lines of an rf-data set. The derivative of the displacement field is equal to the strain in the tissue. Tumors often can be detected by palpation, therefore strain imaging promises to yield good results to detect such tumors. For multicompression strain imaging a sequence of rf-images is acquired under step-wise increasing compression in order to extend the dynamic range and the resolution of the strain estimates [3]. Due to the lateral motion of the insonified object with respect to the axial beam direction the use of a sector probe leads to significant motion artifacts even in a plane strain state. A fast and efficient method for the correction of lateral motion artifacts is described in [4,5]. An efficient method for the fast calculation of strain images is described in [6]. The methods [5] and [6] were used in this paper.

Tissue classification means the segmentation of image data into small segments and the calculation of statistical tissue parameters either obtained from spectrum analysis or texture analysis of the ultrasonic echo data. The parameters are used in combination with known histological findings to construct a classification system which is able to determine the malignancy state within a region of interest [7,8].

In this paper we present a combined system which is able to exploit the benefits of both methods. Our system is able to acquire *in vivo* multi-compression rf-data for the calculation of the tissue strain which is induced by tissue compression in the order of 0.1%. At the same time a Neuro-Fuzzy classification system described in [9] is used to map the tissue malignancy. Histological cross-sections of the gland were used as a gold standard for the construction of the Neuro-Fuzzy classification system. The classification system was trained with more than 30,000 parameter vectors with known histological findings from the histological cross-sections.

METHODS

The strain images were acquired using a commercially available Combison 330 ultrasound system (Kretztechnik GmbH, Austria) with a 7.5 MHz transrectal probe. A multicompression rf-image series including up to 10 images was acquired at discrete levels of tissue compression using the setup described in [3]. The sampling rate was 33 MHz. The data were stored for off-line processing.

A) STRAIN IMAGING

For strain imaging, first the lateral motion within the area of interest was estimated and corrected by a two-dimensional optical flow cross-correlation technique described in [10].

Afterwards the axial strain in the tissue was determined using the time efficient phase root seeking algorithm described in [6].

In a third step the strain images were color-coded and displayed such that dark areas correspond to tissue regions with low strain and bright areas correspond to regions with high strain (Figure 2d).

B) TISSUE CLASSIFICATION

For tissue classification we used the procedure described in [4]. Figure 1 shows a schematic representing the signal processing strategy. 16 common tissue parameters were extracted from the rf-data in over 30,000 segments and stored in a data base.

The data base was then used to train a Neuro-Fuzzy classifier which is based on a first order Takagi-Sugeno system with two outputs classes. The system was initialized by a time efficient mountain clustering method proposed by Yager et al [11]. The segments were approximately 8.64° x 2.9 mm wide which represents 16 a-lines transversally and 128 samples in the axial direction.

The classification system was optimized to recognize malignant tissue areas which are inconspicuous in the B-mode image and other malignant areas which are conspicuous [12].

The classifier threshold was chosen such that 98% of the segments marked as benign represent the gold standard results. Both malignancy classes were coded in dark colors, benign tissue in white (Figure 2b).

C) HISTOLOGY GOLD STANDARD

All investigated patients underwent radical prostatectomy after the examination. Both, the tissue classification images and the strain images were compared to the histological findings obtained from the pathological examination. The histology was used as a gold standard in order to determine the actual tissue state (Figure 2c).

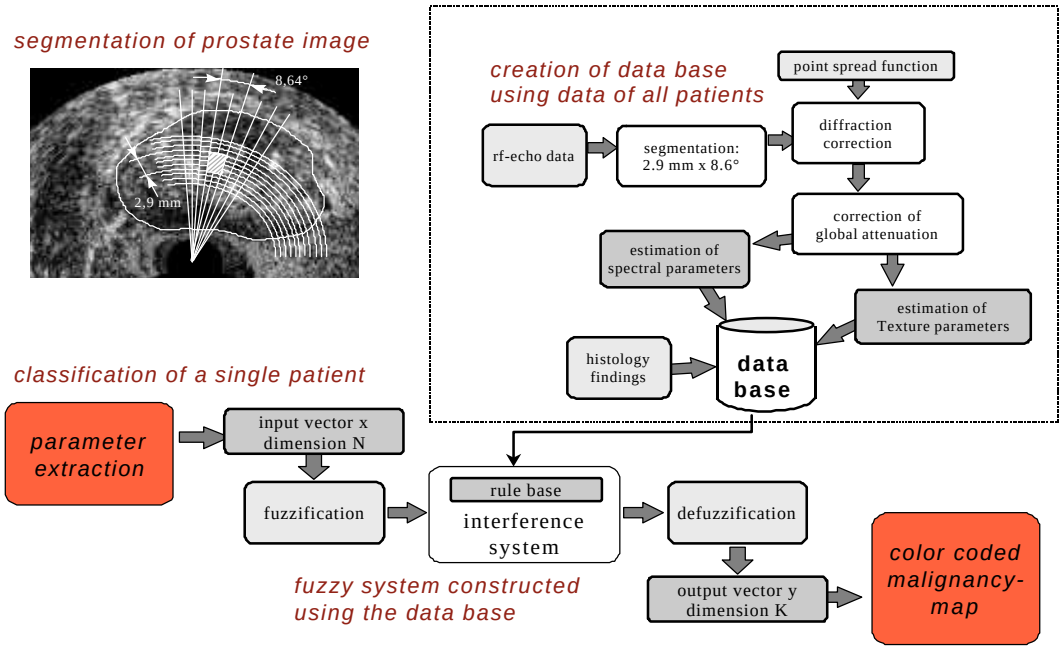

Figure 1: Schematic representing the Neuro-Fuzzy classification approach. A fuzzy interference system is constructed from the data base, i.e. over 30,000 parameter vectors with known histological findings. New patients can classified using the constructed classifier.

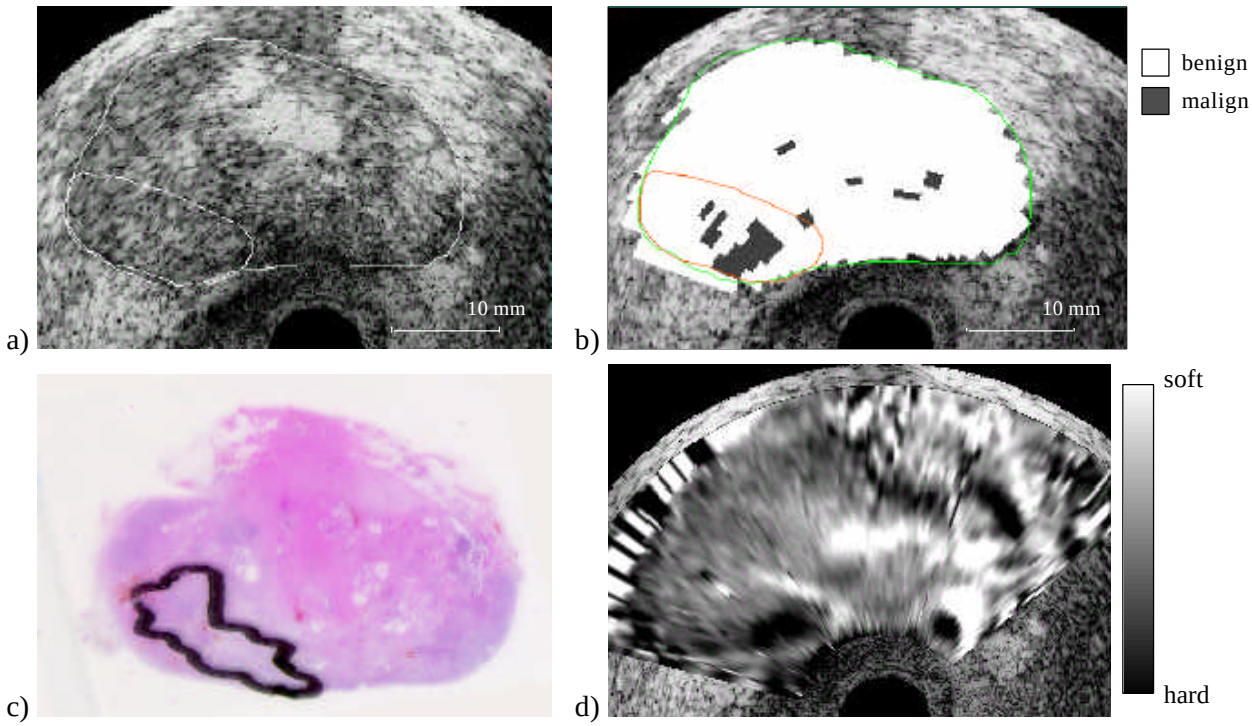

Figure 2: a) B-mode image with marked contours for the carcinoma and the boundary of the gland. The carcinoma is not visible in the B-mode image alone. b) malignancy map obtained from the Neuro-Fuzzy classification system. c) histology with marked carcinoma. d) strain image

RESULTS AND DISCUSSION

Figure 2 shows the comparison of a prostate *in vivo* with the B-mode image, the histology image, the malignancy map, and the corresponding strain image. As can be seen in Figure 2b, the classifier was able to detect partly the carcinoma. There are several dark segments in the corresponding malignancy map which indicate a carcinoma at the left close to the transducer. In the strain image the malignant area is also clearly visible as a dark region surrounded by a high strain artifact on the left hand side close to the transducer. Even though the full extent of the carcinoma is not visible the carcinoma location is clearly visible in contrast to the B-mode image alone. The other dark areas in the strain image are due to calcifications (stones) which can be partly identified by the shadows distally in the B-mode image.

The B-mode image represents a typical ultrasonic prostate image. As in this case carcinomas often can not be identified correctly by the B-mode image alone. With our system we hope to improve the early detection of prostate carcinoma to avoid and/or reduce the number of biopsies taken.

Using a leave-one-out test the overall classification rate of the Neuro-Fuzzy classifier was 60.6% for visually inconspicuous malignant tissue segments and 68.9% for visually conspicuous segments (see [12] for details).

In general the strain images were in good agreement with the histological findings, although no specific recognition rates can be stated yet.

CONCLUSIONS

We presented a new system for the acquisition and display for both tissue characterization and elastographic strain imaging. For preliminary in vivo data both methods show good agree with histology “gold standard”. Due to its real time capability strain imaging promises better applicability in a clinical setting. In the near future we plan to use our real time strain imaging system for data acquisition and tissue classification.

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