Automated detection of prostate cancer using wavelet transform features of ultrasound RF time series

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Extended abstract

According to the American Cancer Society, prostate cancer is the second common type of cancer found in American men (skin cancer is the most common type). Prostate cancer is the second leading cause of cancer death in men (second to the lung cancer). Prostate cancer may be found by testing the amount of prostate-specific antigen (PSA) in blood and digital rectal exam (DRE). Due to noticeable false positive and false negative rates of these tests, a biopsy is necessary for a reliable prostate cancer diagnosis. Transrectal ultrasound (TRUS) –guided biopsy is the most common practice for prostate biopsy. However, most prostate lesions are not easily distinguishable in TRUS images.

Numerous techniques have been proposed for automated detection of prostate cancer tumors [1]. This research addresses the issue of automated detection of prostate cancer tumors in TRUS images using wavelet transform based features of ultrasound radiofrequency (RF) time series. The proposed technique outperforms the previously proposed methods.

Ultrasound RF data used in this research were adopted from a previous study [2]. The data were collected using extracted prostate specimens of 30 patients. Extracted prostates were scanned along transverse planes while suspended in a water bath. The data was collected using a Sonix RP (Ultrasonix Inc., Richmond, BC, Canada) ultrasound machine equipped with a transrectal probe (BPSL9-5/55/10). The central frequency was set to 6.6MHz. RF echo signals were recorded while the probe and the tissue were fixed in position. 112 frames of RF data were acquired at the rate of 22 frames per second from each cross-section of the tissue. The prostate specimens then were dissected along the scanned cross-sections. Histopathological analysis of whole mount slides were acquired and used as the gold standard. The process of registering the histopathology maps to the RF frames was performed manually.

In each cross section, several regions of interest (ROIs) with 1.85×1.87 mm size were chosen. ROIs were selected from 46 cross-sections. 1478 normal and 856 cancerous ROIs were tested for this study. Each ROI was represented by three groups of features, namely, wavelet, spectral and fractal features.

Wavelet features: Samples of RF signals corresponding to a fixed spot of tissue form one RF time-series. Therefore, each time series is a discrete signal with 112 time steps. The time series were analyzed using discrete wavelet transform (DWT). Approximation and detail sequences were extracted using Daubechies-4 wavelet. Approximation and detail sequences of all time series within an ROI were averaged. Averages of approximation and detail sequences of each ROI were used as representative features for the ROI. The features were called Aj and Dj which are the average of approximation and detail sequences at levels j=1,2,3.

Spectral features: Spectral features were extracted as proposed in [2]. Frequency spectrum of each time series was calculated. Frequency spectrum of time-series within an ROI averaged over the ROI. The average spectra were normalized by setting the maximum of the frequency components to one. The first four RF time series features (S1, S2, S3 and S4) were the average value of the normalized spectrum in four quarters of the frequency range. Additionally, a regression line was fitted to the values of the spectrum (versus normalized frequency). The intercept (S5) and the slope (S6) of this line were used as two more features [2].

Fractal dimension (FD): fractal dimension of the RF time series were computed based on the Higuchi algorithm. FD of all the time series within an ROI were averaged and used as a representative feature of the ROI.

In order to classify ROIs into normal and cancerous ROIs, different combinations of above-mentioned features (six wavelet features, six spectral features and one fractal feature) were tested. A support vector machine (SVM) classifier was used to classify the ROIs.

In order to prepare the data set for training and testing, the jackknife approach was utilized in which the ROI features of one patient from the data set were removed and SVM classifier was trained using the rest of the data. Trained SVM was used for classification of the ROIs of the subject whose ROIs had been removed. Then, the classification results were compared with those detected manually. Then, the training and testing process was repeated for all subjects one by one. The jackknife estimates of the classification were averaged between the subjects.

The combination of S2, S3, S4, S5, S6 and FD features were shown to be the best subset of RF time series features tested in [2]. The following table shows the results of 4 selected combinations of 13 features with corresponding accuracy, sensitivity, specificity and the area under ROC curve.

Features	Accuracy	Sensitivity	Specificity	Area under ROC curve
S2, S3, S4, S5, S6, FD	85.7%	85.2%	86.1%	93.1%
A1,A2,A3,D1,D2,D3	61.3%	57.6%	67.9%	57.6%
S2, S3, S4, S5, S6, FD, A1, A2, D1, D2	91.7%	86.6%	94.7%	95.0%
All 13 features	86.8%	74.9%	93.6%	92.8%

As it can be seen wavelet coefficients cannot be considered as an alternative feature set to spectral and fractal features. However, adding this A1, A2, D1, D3 features to previously proposed feature can increase the performance of automated detection of prostate cancer using ultrasound RF time series.

References

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[2] M. Moradi *et al*., “Prostate cancer probability maps based on ultrasound RF time series and SVM classifiers: A large scale in-vitro study,” to appear in the proceedings of MICCAI 2008.