A Novel Computer-Assisted Approach for Prostate Cancer Diagnosis on T2w MRI

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Target Audience: This abstract is targeted at engineers, scientists, clinical radiologists, and urologists who are interested in the development and application of better computer assisted tools for prostate cancer diagnosis/prognosis on MRI.

Purpose: T2w in vivo MRI is a widely used imaging modality for prostate cancer diagnosis. However, detecting prostate cancer on T2w MRI is challenging as the T2w signal intensity of cancerous regions are often very similar to that of normal regions. Even for an experienced radiologist, benign appearing pathologies (e.g. benign prostatic hyperplasia, HGPIN) can mimic he appearance of adenocarcinoma on T2w MRI and hence can be challenging to differentiate. Therefore, there is a need for better computer assisted tools for diagnosing presence of prostate cancer on T2w MRI. In this work we present a computerized multi-scale textural approach to exploit differences in image patterns of adenocarcinoma compared to normal, benign regions.

Method: Two separate T2w MRI cohorts were assembled from two different institutions: (1) **D1** This dataset consists of in vivo T2w MRI images collected from 16 subjects who were diagnosed with prostate cancer. The axial T2w imaging was performed with 3 mm slice thickness and 1.0 mm gap. Imaging FOV was 14 cm, and acquisition matrix size was 256 by 128-179. Careful co-registration was performed between digitized histological images and these in vivo MRI slices to map prostate cancer annotations via the following two steps. Step 1: Correspondences between T2w MRI and histologic slices were identified by expert radiologist and pathologist based on distances between slices and major anatomical landmarks. Step 2: Histologic images were registered to T2w MRI slices by using a thin plate spline registration approach to map the histologic annotations onto MRI. (2) **D2** This dataset comprised 22 patient studies, all of whom had been previously diagnosed with prostate cancer and had subsequently undergone radical prostatectomy. Similar to D1, deformable coregistration was applied to non-linearly align the pre-operative MRI with the post-operative histologic sections to map spatial extent of cancer onto corresponding MRI sections. Three local image features, *Gabor [1], Haralick [2], and PHOW (Pyramid Histogram of Visual Words) [3]*, are extracted at the scales of 3x3, 5x5 and 7x7, as the quantitative representation of each individual sample (see Figure 1). An optimization problem, which aims at best separating the features of cancerous pixels from these of normal pixels, is designed to rank the importance of the three scales. Salient scales are the top-ranked ones, only at which the extracted features are retained for training a machine learning classifier. The same types of image features are extracted for each pixel on a test image, but only at the learned salient scales. Each pixel is individually classified via the learned classifier, to yield a probability score indicating the likelihood of belonging to normal and cancerous region. Majority voting within each superpixel is finally applied to smooth the resultant probability map, refining the prediction of prostate cancer. D1 and D2 are alternatively used as training and testing set for testing the role of salient feature scale learning.

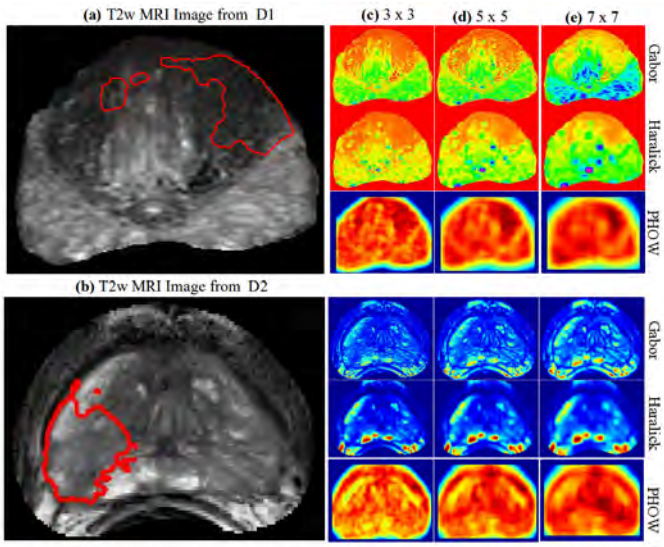

Figure 1. Illustrating the two dataset and multi-scale features. In this example, three texture features, *Gabor, Haralick,* and *PHOW (Pyramid Histogram of Visual Words)*, are extracted at the window sizes of **(c)** 3x3, **(d)** 5x5, and **(e)** 7x7, as the computerized representations of **(a)** and **(b)** T2w MRI image, respectively. Multiple scales are needed since it is extremely difficult to visually identify the distinctive scales at which the annotated cancerous regions in **(a)** and **(b)** are distinguishable.

Method	Learned Scales		Area under ROC curve		Average feature extraction time
Proposed scale learning	Gabor	3 x 3	D1→D2	0.646	93.3 seconds
	Haralick	5 x 5			
	PHOW	7 x 7	D2→D1	0.653	
Multi-scale features	N/A		D1→D2	0.639	281.9 seconds
			D2→D1	0.647	
Intensity	N/A		D1→D2	0.518	N/A
			D2→D1	0.475	

Table 1. Using learned scales vs multi-scale features for pixelwise prostate cancer detection on T2w MRI images. The performance is compared in terms of the AUC (area under ROC curve) value and the feature extraction time per image.

Results: The proposed prostate cancer detection method is compared with a baseline scheme using raw intensity, and an alternative scheme using features from all the three scales. The results summarized in Table 1 show that (1) local image features are more robust than raw intensity in cancer identification, (2) Different image feature tends to has a different salient scale, and for Gabor, Haralick and PHOW, it is 3x3, 5x5, 7x7, respectively, (3) Compared to using multiple scales, using salient scale improves the classification performance (AUC value), and also significantly reduces the computational time, (4) The scale selection scheme is resilient to differences in imaging data acquired from the two different sites.

Concluding Remarks: The proposed approach is a novel computer assisted approach for prostate cancer diagnosis on in vivo T2w MRI. It well solves the problem of extracting computerized image features at multiple scales from T2w MRI. The results presented appear to suggest a higher accuracy and lower computational time compared to using T2w MRI intensity and exhaustive multi-scale features.

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