Investigation of Abnormal Prostate Region Detection Using Different Modality Combinations of mpMRI Scans

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Introduction

There are many prevention programs in effect for various organ cancer nowadays and prostate cancer is not an exception. Prostate cancer is the second most widespread following lung cancer and the fifth most common cause of cancer death amongst men worldwide according to World Cancer Research Fund International. Statistics show high prostate cancer morbidity and mortality rates, which stress the relevance of the problem. Lithuania has adopted a law for funding a program for early prostate cancer diagnosis on a national level in 2005. Despite biopsy being the only way to conclude a definite diagnosis of prostate cancer, it still misses up to 30% of clinically significant caner and the reason for that is taking samples from wrong location. This usually leads to repeated biopsy which in turn increases the risk of possible side effects such as temporary erectile dysfunction and urinary problems. Latest recommendations from the National Comprehensive Cancer Center include the usage of multiparametric magnetic resonance imaging (mpMRI) for diagnosing, characterizing and staging of prostate cancer. Multi parametric magnetic resonance imaging can be used to determine the location to perform biopsy on, reducing both the number of samples needed to detect prostate cancer and the chance of needing repeated biopsy test. The fact that there is a lack of high-resolution images as well as not standardized magnetic resonance imaging signal intensity burdens the problem of computer-aided diagnosis.

According to Prostate Imaging Reporting and Data System (PI-RADS) v2 abnormal prostate areas must be found in at least three different scans of mpMRI to diagnose prostate cancer: T2-weighted (T2W), diffusion-weighted (DWI) and apparent diffusion coefficient (ADC). Other scans such as or magnetic resonance spectroscopy (MRS) can have additional side effects on patients or require better MRI machines which in turn increases the cost of test, also they are not present in many institutions, therefore are mostly used in scientific researches and not in daily practice. Otherwise such areas are only treated as suspicious and need further tests.

Dataset

Multiparametric magnetic resonance images were gathered for 146 cases out of 10 different institutions throughout Lithuania and labelled by experts at National Cancer Institute. The fact that mpMRI is not standardized leads to images of different resolution as well as different intensity values due to different protocols used during scanning. One of parameters for DWI scan is so called b-value, which reflects the strength and timing of the gradients used to generate diffusion-weighted images. The higher the b-value, the stronger the diffusion effects as well as more artifacts. Different institutions use different protocols resulting in collected DWI images of different b-values: 0 and 2000 in one institution and 100, 300, 800 and 1500 in another one. Highest recorded b-value was 2000. ADC scans are in turn calculated from acquired DWI scans with lowest and highest b-values using the formula:

$$ADC = -\ln(S_i / S_1) / (b_i - b_1),$$

where S_i and S_1 are DWI images with highest and lowest b-values respectively and b_i and b_1 are b-values themselves. The formula is applied on a pixel basis. In order to align DWI scans, the reverse of this formula was used to calculate images with b-values of 0-4000 with a step of 100:

$$S_i = S_1 \times \exp[-(b_i - b_1) \times ADC].$$

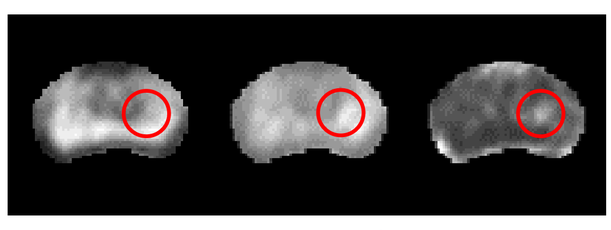

Figure 1. Calculated DWI scans with b-value of 0, 2000 and 4000 from left to right respectively. Red circle marks diagnosed cancer.

Experiment

Deep neural networks using models with different combinations of mpMRI scans were created. Each mpMRI scans combination resulted in 2 flavours of neural networks being created: 2 dimensional one and 3 dimensional. Each network was trained using a 5-fold cross validation with dice similarity coefficient as accuracy metric. Data augmentation was applied on the fly using different techniques such as random scaling, random rotation, elastic deformations and gamma augmentation.

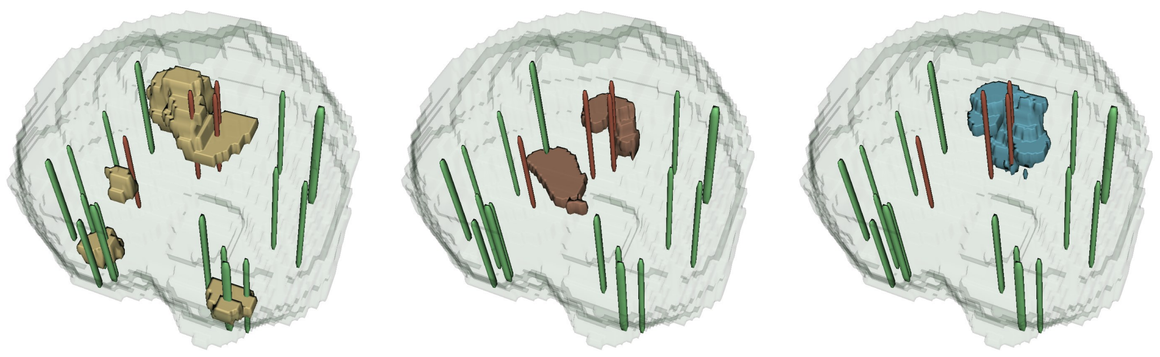

Figure 2. Segmentation example. Yellow - reference segmentation, brown - 2D network segmentation, blue - 3D network segmentation. Bars depict biopsy results: malignant samples in red, benign and no cancer samples in green.

Table 1. Segmentation results

Scans used	2D	3D
T2W, DWI, ADC	0.363	0.399
T2W, cDWI-b4000, cADC	0.314	0.373
T2W	0.135	0.193
T2W, DWI	0.321	0.407
T2W, ADC	0.253	0.330
T2W, cDWI-b4000	0.309	0.372
T2W, cADC	0.238	0.303
T2W, cDWI-b2000	0.321	0.342
T2W, cDWI-b1000	0.223	0.335
T2W, DWI, ADC, cDWI-b0— cDWI-b4000, cADC	0.335	0.358
T2W, cDWI-b0— cDWI-b4000, cADC	0.345	0.367

Conclusions

1. Models containing any type of DWI scan perform better than models with T2W only or combination of T2W and ADC;
2. Both DWI and ADC scans are needed for 2 dimensional models, however ADC scans add overhead for 3 dimensional models and reduce segmentation accuracy;
3. Increasing b-value for calculated DWI increases segmentation accuracy;
4. 3 dimensional models work better when segmenting cancerous prostate zones, despite 2 dimensional models performing better when segmenting prostate itself as shown in previous work.

Future Work

1. Training deep neural networks on biopsy confirmed cancer zones;
2. Investigating if T2W scans add value when segmenting cancerous prostate zones;
3. Adding additional scans to the models such as dynamic contrast-enhanced time series;
4. Creating a tool to help in diagnosing prostate cancer including the pipeline of both prostate and cancerous regions segmentation.