Quantitative Investigative Analysis of Tumour Separability in the Prostate Gland using Ultra-high b-value Computed Diffusion Imaging

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Abstract

High *b*-value diffusion-weighted imaging is a promising approach for diagnosing and localizing cancer in the prostate gland. Due to hardware limitations, an alternative approach is computed diffusion-weighted imaging, which allows for estimation of ultra-high *b*-value images from a set of diffusion-weighted acquisitions with different magnetic gradient strengths. This paper presents a quantitative investigative analysis of the improvement in tumour separability using ultra-high *b*-value computed diffusion-weighted imaging.

Introduction

- There were 913,000 new diagnoses of prostate cancer globally in 2008
- Localization of prostate cancer is particularly important for treatment using minimally-invasive focal therapy technologies

Problem

- Diffusion-weighted imaging (DWI) can be used to differentiate between healthy and cancerous tissues in the prostate gland using a diffusion gradient (with specific *b*-value)
- Prostate tumour identifiable in diffusion weighted images with a high *b*-value
- Due to hardware limitations, difficult to achieve high *b*-value at a high signal-to-noise ratio

Objective

To investigate and quantify the benefits of ultra-high *b*-value computed diffusion imaging for prostate cancer detection.

Computed Diffusion-Weighted Image Methodology

- ADC value (A) for a particular voxel is estimated using a set of diffusion-weighted images measured with different *b*-values (b_i and b_α)

$$S_i = S_\alpha e^{-(b_i - b_\alpha)A}$$

- If a collection of DWI images (S) is used, the ADC estimate is formulated as a Bayesian estimation problem

$$\hat{A} = \arg\max_A P(S|A)$$

where $P(S_i|A) \sim N(S_\alpha e^{-(b_i - b_\alpha)A}, \sigma^2)$

- The ADC estimate $\hat{A}$ can be used to compute diffusion-weighted images S_i at any desired b-value b_i

$$S_i = S_\alpha e^{-(b_i - b_\alpha)\hat{A}}$$

Experimental Results

Expected Probability of Error

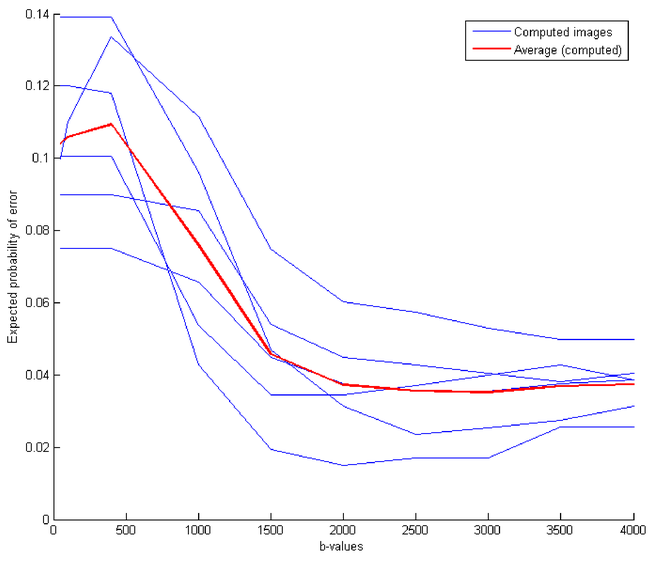
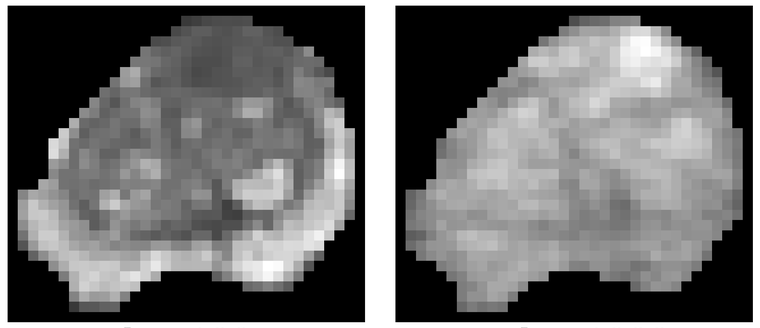


Fig. 1: The expected probability of error curves suggest improvements for a wide range of *b*-values past 1500, with an optimal choice in the neighbourhood of 3000.

Example Patient Case



b = 100 b = 1000

Computed b =3000 Computed b = 4000

Fig. 2: Patient case showing observed diffusion-weighted images for lower b-values and computed diffusion-weighted images for higher *b*-values

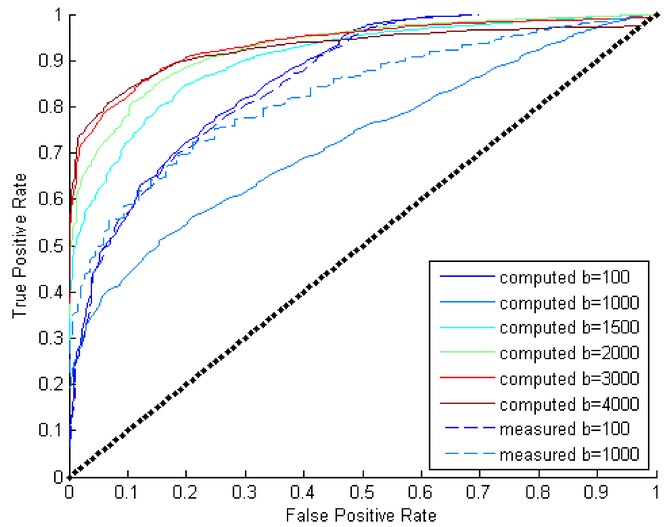


Fig. 3: Receiver Operator Characteristic curve for the patient case showing good classification for higher *b*-value computed diffusion-weighted images

Acknowledgements

This work was supported by the Natural Sciences and Engineering Research Council of Canada and the Ontario Ministry of Economic Development and Innovation.

NSERC CRSNG