

APPARENT DIFFUSION COEFFICIENT ESTIMATION IN PROSTATE DW-MRI USING MAXIMUM LIKELIHOOD

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Introduction: Prostate cancer is the most common cancer among men. Diffusion weighted magnetic resonance imaging (DW-MRI) used in combination with T2-weighted MRI is of interest to diagnose cancer. Apparent diffusion coefficient (ADC) values have been tried as threshold for detection of tumour, but also have been related to tumour grade [1]. However the creation of ADC maps from diffusion weighted images is usually achieved using the least squares (LS) fitting method, which does not account for the noise in magnitude MR data. An alternative approach using maximum likelihood (ML) for rician distributed data points [2] produces unbiased estimates of ADC. This study investigates the possible benefits of using this fitting method in clinical routine.

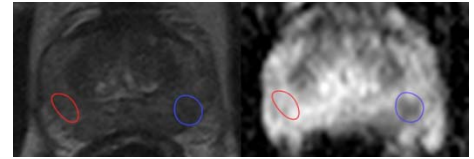


Fig. 1: Example of patient data, T2 map (Left) and ADC map (Right), with ROIs for non-cancerous tissue (red) and tumour (blue)

Method: The signal magnitude in DW-MRI imaging follows an exponential decay: $S(Bvalue|ADC, S_0) = S_0 \exp(-ADC \times Bvalue)$. The first experiment consisted of 1D signals with ADC in $[0.9, 3] \text{ mm}^2/\text{s}$ corrupted with rician noise, with SNR in $[1, 10]$ (the SNR taken as reference being that of the image at B-value = 0). For each couple (ADC, SNR), 10000 signals were generated and fitted using LS and ML with signal magnitudes at B-values of 0, 150, 500 and 1000 s/mm². Then, simulated DW-MR data, representing tumour tissue (T) surrounded by healthy prostate peripheral zone (PZ), were generated using ADC values taken from previous study [3] ($ADC_{PZ} = 0.0015 \text{ mm}^2/\text{s}$ and $ADC_T = 0.0009 \text{ mm}^2/\text{s}$) and the same B-values as in the previous experiment. S_0 values were taken from patient data ($S_{0PZ} = 0.34 \pm 0.0024 \text{ mm}^2/\text{s}$ and $S_{0T} = 0.26 \pm 0.0085 \text{ mm}^2/\text{s}$), along with an estimate of the rician noise level so that realistic SNR could be introduced in the simulations. Tests were run with varying size for the tumour region of interest (ROI) and repeated 150 times. A set of 18 prostate DW-MR images along with the corresponding T2 weighted scans from patients diagnosed with prostate cancer, were used to quantify the difference between ML and LS estimates. For each dataset, ROIs corresponding to tumour and non cancerous tissue (Fig. 1) were contoured by a radiologist with 5 years experience in prostate MRI. Finally, for each dataset, ADC maps generated with both LS and ML were showed in random order to two radiologists to evaluate potential visual difference between the two approaches. Radiologists were asked to specify on which map (if any) the tumour region was the most clearly appearing.

Results: ML generally provided significantly less biased estimates than LS. Fig. 2 shows representations of estimates obtained with both methods with respect to the ground truth. The underestimation of ADC clearly appears for LS along with sensitivity to SNR variations, whereas ML shows a better accuracy and a bigger robustness to low SNR. Fig. 3 shows an example of median error of estimates with respect to the ground truth value of ADC for varying SNRs. Concerning the experiment with simulated data, the average errors of ML median estimates were always below 3% for the PZ ROI and below 8% for the tumour ROI when the tumour region was larger than 40 pixels, whereas that of LS median estimates were always between 8 and 10% in the same conditions. Results from patient data showed an average increase of 13% between ML and LS estimates in tumour ROIs from real data (compared to 14% for simulated data with similar SNR) and an average increase of 9.8% in normal PZ ROIs (compared to 8.3% for simulated data). Fig. 4 presents a comparison between estimates obtained with real data and simulated data. The real data estimates are generally close to the corresponding simulation, suggesting that previous experiments were realistic and confirming the better performance of ML compared to LS. For the visual experiment, radiologists preferred the ML ADC map in 28% of the cases, the LS ADC map in 36% and did not have a preference in 36% of the cases.

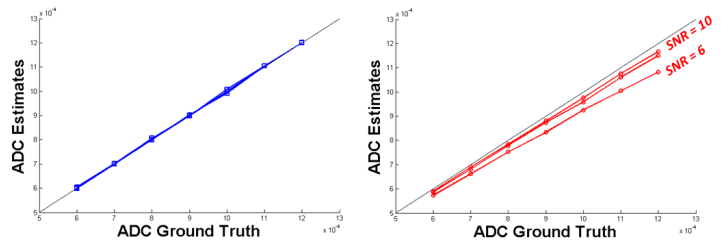


Fig. 2: Representation of ML (left) and LS (right) estimates with respect to the true ADC values for SNR = [6, 10]

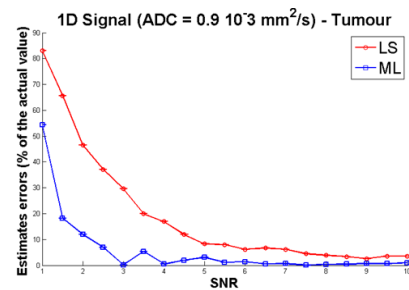


Fig. 3: simulations at typical tumour ADC value. It shows the median of absolute error of estimate expressed as a percentage of the ground truth value for various SNR

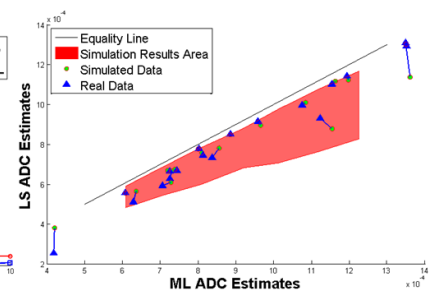


Fig. 4: Comparison of ADC estimates obtained with real and simulated data. Simulation area covers a realistic range of SNRs and ADCs in tumour ROIs

Conclusion: We studied the estimation of ADC using maximum likelihood as an alternative to the least squares algorithm in the case of prostate cancer. It was shown, based on simulated and patient data experiments that ML yields more reliable estimates, thus it may help in application of thresholds for detection of disease and to predict tumour grade - without impacting on visual quality of ADC maps that are used by radiologists of qualitative clinical assessment.

[1] S. Verma *et al.* Assessment of aggressiveness of prostate cancer: Correlation of apparent diffusion coefficient with histologic grade after radical prostatectomy. *AJR*, 196:374–381, 2011

[2] S. Walker-Samuel *et al.* Robust estimation of the apparent diffusion coefficient (ADC) in heterogeneous solid tumors, *MRM*, 62(2):420–429, 2009

[3] N.M. deSouza *et al.* Diffusion-weighted magnetic resonance imaging: a potential non invasive marker of tumour aggressiveness in localized prostate cancer, *Clinical Radiology*, 63:774–782, 2008