Prostate Cancer Detection from Model-free T1-weighted Time Series and Diffusion Imaging

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Introduction

- The combination of Dynamic Contrast Enhanced (DCE) images with diffusion MRI has shown great potential in prostate cancer detection[1,2].
- Parameterization of DCE images to generate cancer markers is traditionally performed based on pharmacokinetic (PK) modeling , which makes simplistic assumptions about the tissue perfusion process, and requires the knowledge of contrast agent concentration in a major artery.
- Model-free approaches have shown potential in prostate cancer diagnosis [3,4].

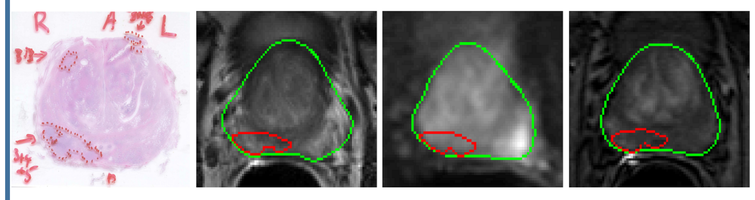
Our Approach

- To *learn* the perfusion pattern directly from the DCE time course without pharmacokinetic modeling and to apply it in a multi-parametric MRI (mp-MRI) framework.

Data

- 16 radical prostatectomy patients (49-69 years, with Gleason grades 3+3, 3+4 and 3+4+5)
- 3T MRI before surgery, sectioning device ensured good correspondence between histology and MRI slices [5].
- Prostatic carcinoma outlined by an anatomic pathologist with over 20 years of experience.

Registration



(a) (b) (c) (d)

(a)Peripheral zone tumor of Gleason Grade (3+4+5) from pathology slide is mapped to the corresponding (b)T2-W, (c)DTI and (d)DCE-MRI slice using affine transformation followed by B-spline registration.

Features Extraction & Classification

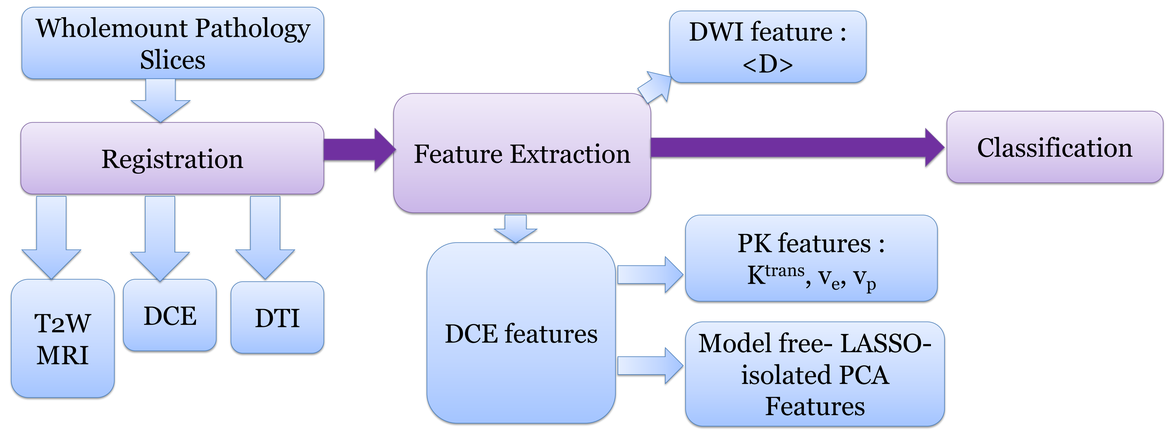
- Intensity values within each tumor were averaged to form an average time course signal.
- Principal component analysis was performed on the average time course signal and PCA components ranked according to the magnitude of their LASSO coefficient.
- L1-norm regression problem : $\hat{\beta} = \arg min_{\beta} \left(\frac{1}{2} \sum_{j=1}^{N} \left(y_j - \beta_0 - \sum_{k=1}^{p} I_{jk} \beta_k \right)^2 + \lambda \sum_{k=1}^{p} |\beta_k| \right)$; I is the PCA components, y_j is label for j[th] ROI, λ is the regularization parameter, β includes the LASSO coefficients.
- Number of PCA features to be included is determined by forward search to maximize Area Under Receiver operating characteristic curve (AUC).
- Soft margin Support Vector Machine (SVM) is used, parameters tuned by leave-one-patient-out cross validation to maximize AUC.

References

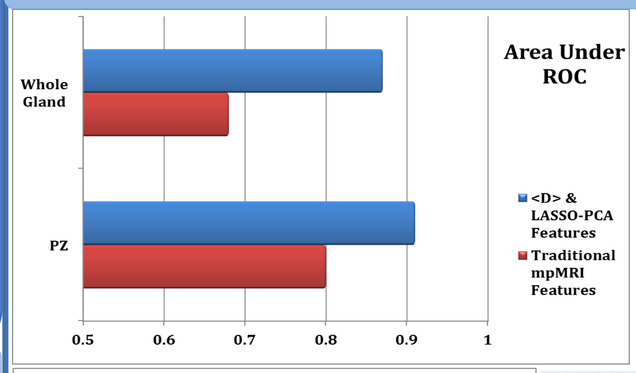
[1] Hegde *et al.*, JMRI 2013;37(5):1035–1054; [2] Moradi *et al.*, JMRI 2012, 35(6):1403-1413; [3]Eyal *et al.*, Inv Rad 2010, 45(4):174-181; [4] Haq et al., CMIG 2014; doi: 10.1016/j.compmedimag.2014.06.017; [5] Drew *et al.*, JMRI 2010, 32:992-996.

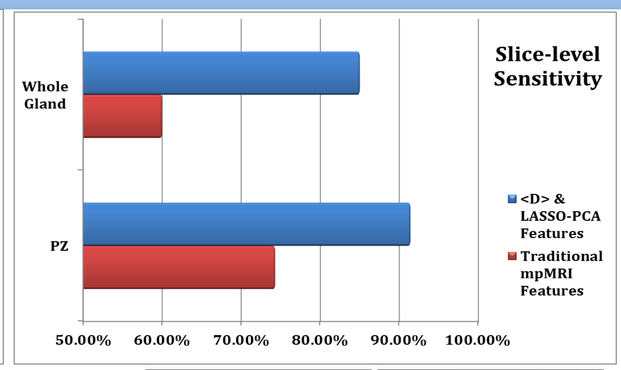
NSERC CRSNG CIHR IRSC

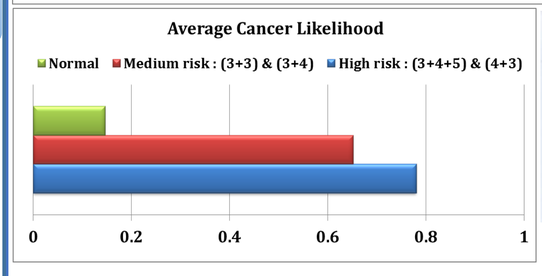
Framework

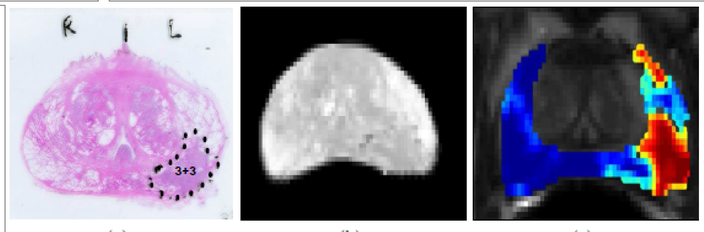


Result



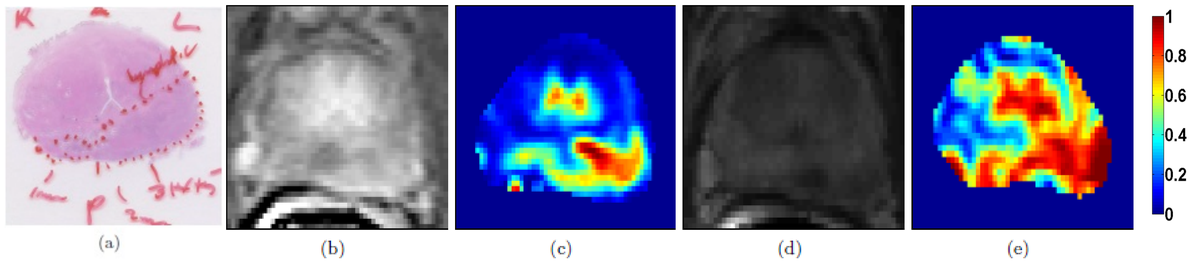






(a) (b) (c)

(a) Peripheral zone tumor marked in pathology slide (b) Pathology slide registered to the corresponding T2-W image. (c) Generated cancer likelihood map (by the PZ classifier) superimposed on the T2-weighted image.



(a) (b) (c) (d) (e)

(a) Peripheral zone tumor marked in pathology slide (b) Corresponding DCE image. (c) Cancer likelihood map generated using the classifier trained on data-driven DCE features only. (d) Corresponding T2-W image. (e) Cancer likelihood map generated using the classifier trained on the proposed mpMRI features, registered to T2-weighted image.

Conclusion

- An image processing pipeline to detect peripheral prostate cancer from mpMRI using data-driven DCE features is developed.
- Cancer likelihood maps were generated for the whole prostate gland that showed higher cancer likelihood in cancerous regions.