A Boosting Approach for Prostate Cancer Detection using Multi-Parametric MRI

Quality Control by Artificial Vision
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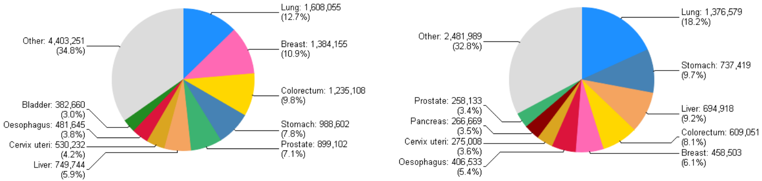
Introduction
Motivations

Statistics



(a) # of cancer cases

(b) # of cancer deaths

Implications

- 2^{nd} most frequently diagnosed men cancer
- Accounting for 7.1% of overall cancers diagnosed
- Accounting for 3.4% of overall cancers death

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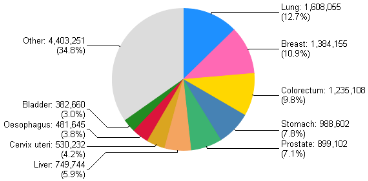
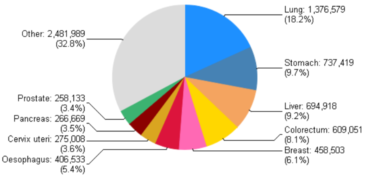


(a) # of cancer cases



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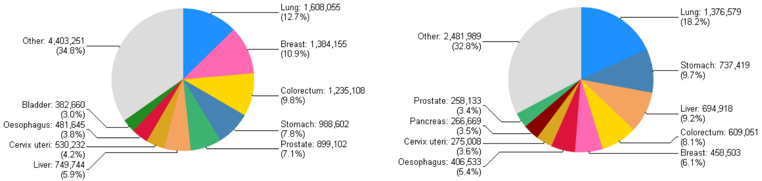

(a) # of cancer cases (b) # of cancer deaths

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Introduction
Screening

PSA level

→ Checking for a higher-than-normal PSA level

✗ Not reliable

"Blind" TRUS biopsy

→ Take several samples through biopsy at different prostate locations

✗ Invasive procedure

✗ Lead to false positives & negatives

Current trendy techniques: MRI

✓ Non-invasive technique

✗ Need further investigations regarding the potential of the different MRI modalities available

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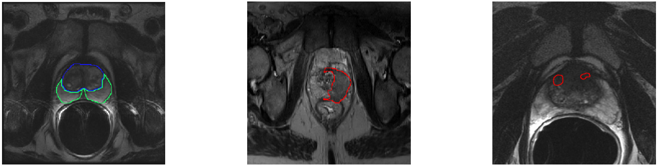
Introduction
MRI modalities

T_2W MRI



(a) Healthy (b) CaP PZ (c) CaP CG

Features for CaP

- Low-SI
- Ill-defined shape

Introduction
MRI modalities

DCE MRI

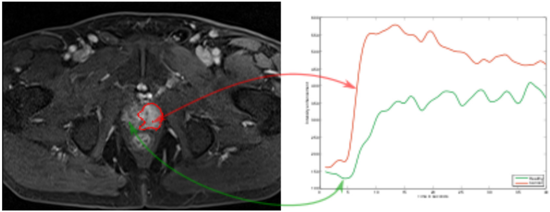


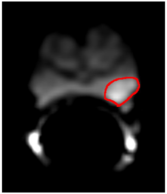
Figure : Green: healthy - Red: CaP

Features for CaP

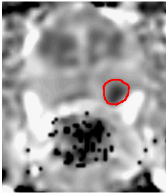
- Faster wash-in, wash-out, time-to-peak enhancement
- Higher integral under the curve, max SI

Introduction
MRI modalities

DW MRI - ADC



(a) DW MRI



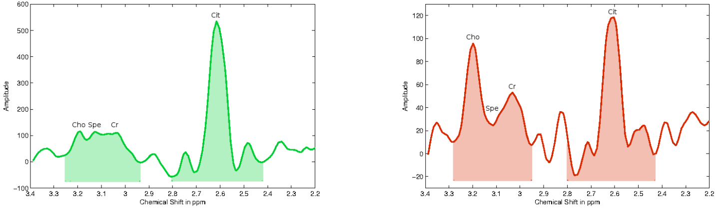
(b) ADC

Features for CaP

- DW MRI - Higher SI
- ADC - Low-SI

Introduction
MRI modalities

MRSI



(a) Healthy

(b) CaP

Features for CaP

- Decrease of citrate and spermine
- Increase of choline

The Medical Imaging evil

The reasons of a nightmare

→ Multidisciplinary competences: medical doctors vs. computer scientists

Some examples

- Delay in the data acquisition
- Interest differences between the different core competences

→ Lack of interest

The keystones needed

- Common datasets
- Algorithms comparisons
- Full benchmarking

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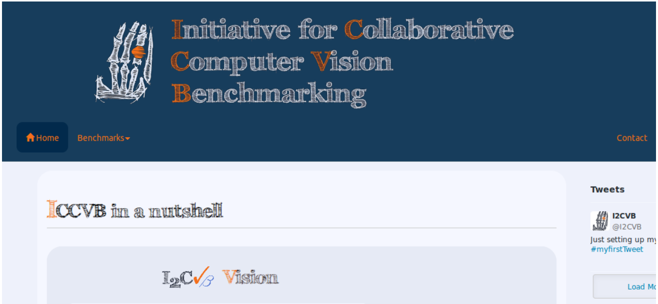
Overview

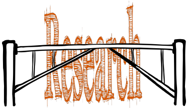
I2CVB Platform



- Development of a web platform

Manifesto

I2CVB Vision

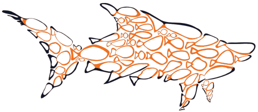


- Democratization of the ability to research

I2CVB Mission

- Open data; evaluation methods; comparison framework; reporting platform

I2CVB Protagonists



- Research groups and individuals from all walks of life to shape a transparent community

I2CVB Strategy

- Transferring successful practises from Free Software and Quality Management

I2CVB
Prostate dataset

Multi-parametric MRI

- Cohort of 20 patients
- T_2W MRI, DCE MRI & ADC
- 3 Tesla whole body MRI without endorectal coil

Ground-truth

- Delineations: prostate - zones - CaP
- Healthy: 2 *vs.* CaP: {PZ: 13, CG: 3, PZ + CG: 2 }

Classification framework

Pre-processing

- Resampling data to T_2W MRI dataset
- Balancing data using random sampling without replacement

$\rightarrow$ 218,423 voxels

Features extraction

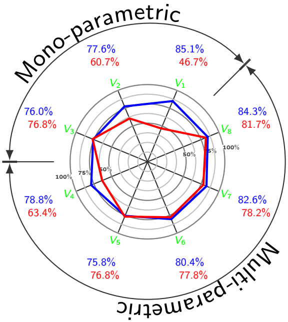
- Voxel-based "$V(\cdot)$": intensities of T_2W MRI, ADC, DCE MRI & zonal information (PZ *vs.* CG)
- 3D-texton-based "$T(\cdot)$": $(9 \times 9 \times 3)$ intensities of T_2W MRI, ADC, DCE MRI & zonal information (PZ *vs.* CG)

Features classification

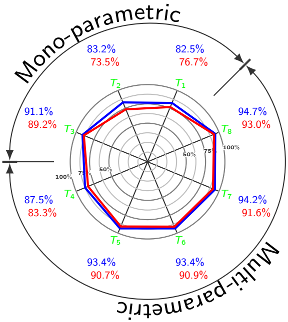
$\rightarrow$ Gradient Boosted Trees classifier

Results

Sensitivity & Specificity



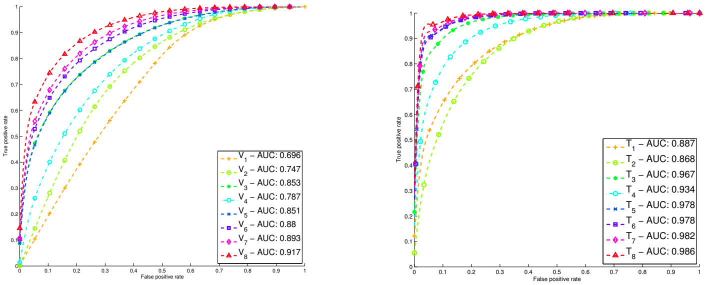
(a) Voxel-based



(b) 3D-texton-based

Results

ROC curves



(a) Voxel-based

(b) 3D-texton-based

Conclusion

Discussions

- DCE MRI is the most disciminative feature
- Combinations of all the modalities lead to better performance
- 3D-texton and neighbourhood information significantly improve the performance

Future works

- Normalisation of the data in a patient-based fashion
- Use more complex features
- Perform LOPO cross-validation
- Perform a full benchmark study of the current methods!!!!

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