Computer-Aided Diagnosis for Prostate Cancer using mp-MRI

PhD Defence
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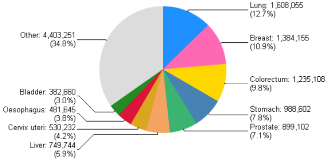
1. Introduction
    - Motivations
    - The prostate organ
    - Prostate carcinoma
    - Screening
    - CAD and mp-MRI
    - Research objectives

2. State-of-the-art

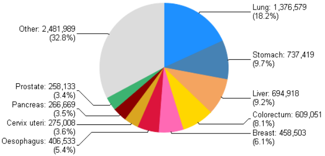
3. I2CVB

Motivations

Statistics



(a) # of cancer cases



(b) # of cancer deaths

Implications, image source[1]

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

[1] J. Ferlay et al. "Estimates of worldwide burden of cancer in 2008: GLOBOCAN 2008". In: *Int. J. Cancer* 127.12 (Dec. 2010), pp. 2893–2917.

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The prostate organ

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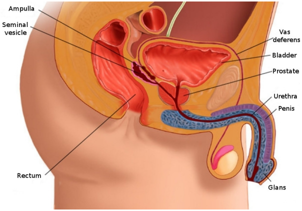
Anatomy



Localization of the prostate organ, image source[2]

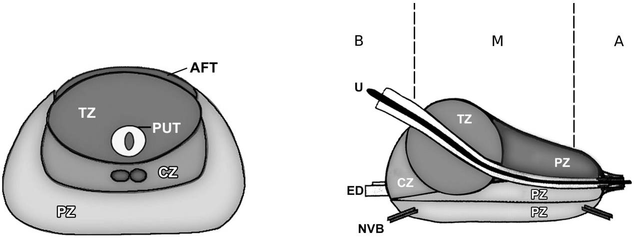
Characteristics

- Height: 3 cm
- Depth: 2.5 cm
- Weight: 7 g to 16 g

[2] Geckomedia. *Natom Anatomy*. French. June 2011. url: http://www.natomshop.com/.

The prostate organ

Anatomy

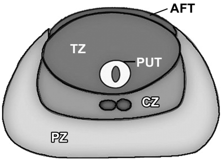


(a) Transverse plane (b) Sagittal plane

Prostate zones - AFT: anterior fibromuscular tissue, CZ: central zone, ED: ejaculatory duct, NVB: neurovascular bundle, PUT: periurethral tissue, PZ: peripheral zone, U: urethra, TZ: transitional zone, B: base, M: median, A: apex; image source[3]

[3] Y. J. Choi et al. "Functional MR imaging of prostate cancer". In: *Radiographics* 27 (2007), pp. 63–75.

Prostate carcinoma (CaP)



CaP development

- Slow-growing → 85 %
- Fast-growing → 15 %
- CaPs in CG are more aggressive

Zonal predisposition

- PZ → 70 % to 80 %
- TZ → 10 % to 20 %
- CG → 5 %

Goals

- Detect CaP
- Distinguish slow- from fast-growing CaP
- Active surveillance *vs.* prostatectomy/other treatments

Screening

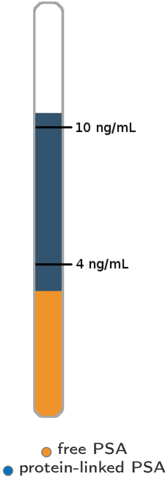
Prostate-specific antigen

- $> 10\,\mathrm{ng\,mL^{-1}} \rightarrow$ biopsy
- From $4\,\mathrm{ng\,mL^{-1}}$ to $10\,\mathrm{ng\,mL^{-1}}$

  $\rightarrow \frac{\bullet}{\bullet + \bullet} > 15\% \rightarrow$ biopsy
- ✗ Not reliable

"Blind" transrectal ultrasound biopsy

- Take samples from different locations
- Grade using Gleason score
- ✗ Invasive procedure
- ✗ Lead to false positives & negatives



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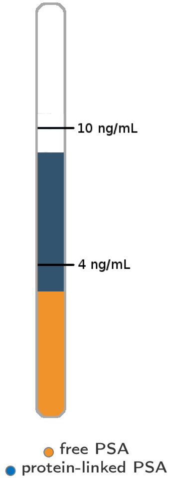

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Screening

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  $\rightarrow \frac{\textcolor{orange}{\bullet}}{\textcolor{orange}{\bullet} + \textcolor{blue}{\bullet}} > 15\% \rightarrow$ biopsy
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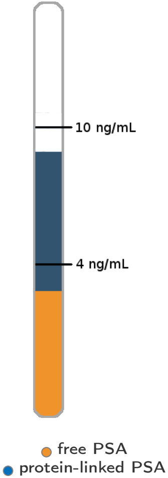

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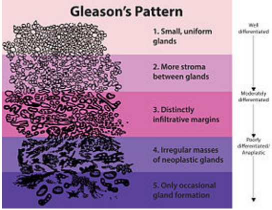

Image source: `https://goo.gl/fEVQXQ`

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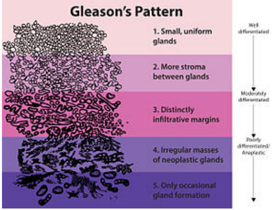

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Pros

- ✓ Reduce CaP-related mortality from 21 % to 44 %[4]

Cons

- ✗ Up to 30 % of over-diagnosis[5]
- ✗ Up to 35 % of undiagnosed CaP[6]
- ✗ Biopsies are invasive

[4] Fritz H. Schröder et al. "Prostate-cancer mortality at 11 years of follow-up". In: *New England Journal of Medicine* 366.11 (2012), pp. 981–990.

[5] G. P. Haas et al. "Needle biopsies on autopsy prostates: sensitivity of cancer detection based on true prevalence". In: *J. Natl. Cancer Inst.* 99.19 (Oct. 2007), pp. 1484–1489.

[6] A. V. Taira et al. "Performance of transperineal template-guided mapping biopsy in detecting prostate cancer in the initial and repeat biopsy setting". In: *Prostate Cancer Prostatic Dis.* 13.1 (Mar. 2010), pp. 71–77.

CAD and mp-MRI

Current trendy techniques: mp-MRI

✓ Less invasive technique

Human diagnosis using mp-MRI

✗ Need further investigation of the mp-MRI modalities

✗ Low repeatability
- Observer limitations
- Complexity of clinical cases

Emergence of CAD

- CADe → detection of potential lesions
- CADx → diagnosis regarding those lesions

UdG

Research objectives

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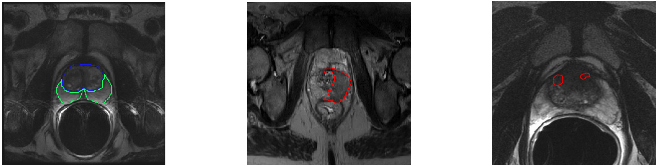
Propose a mp-MRI CAD for CaP

- Study and investigate the state-of-the-art on MRI CAD for CaP
- Identify the scientific barriers
- Design a mp-MRI CAD addressing these issues
- Investigate and analyze the proposed CAD

1. Introduction
2. State-of-the-art
   - MRI modalities
   - CAD for CaP
3. I2CVB

MRI modalities

T_2W-MRI



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

Healthy

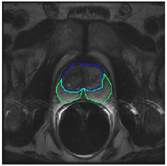
- Intermediate to high-signal intensity (SI) in PZ
- Low-SI in CG

CaP

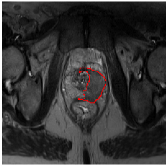
- Low-SI
- Round and ill-defined mass in PZ
- Homogeneous with ill-defined edges in CG

MRI modalities

T_2W-MRI



(d) Healthy



(e) CaP PZ

(f) CaP CG

Pros

- Highest spatial resolution
- Anatomy nicely depicted

Cons

- Low sensitivity in CG
- Lower specificity due to outliers

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MRI modalities

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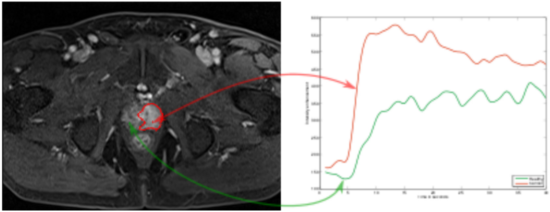
DCE-MRI



Green: healthy - Red: CaP

Healthy

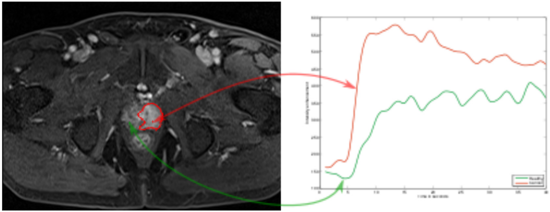
- Slower wash-in, wash-out, time-to-peak enhancement
- Lower integral under the curve, max SI

CaP

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

MRI modalities

DCE-MRI



Green: healthy - Red: CaP

Pros

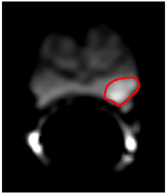
- Information about vascularity

Cons

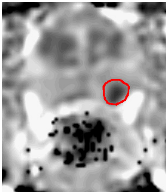
- Spatial mis-registration
- Lower spatial resolution than T_2W-MRI
- Difficult detection in CG

MRI modalities

DW-MRI - ADC



(a) DW MRI



(b) ADC

Healthy

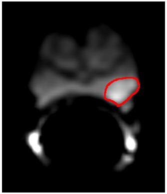
- DW-MRI: lower SI
- ADC: higher-SI

CaP

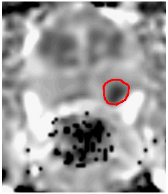
- DW-MRI: higher SI
- ADC: lower-SI

MRI modalities

DW-MRI - ADC



(c) DW MRI



(d) ADC

Pros

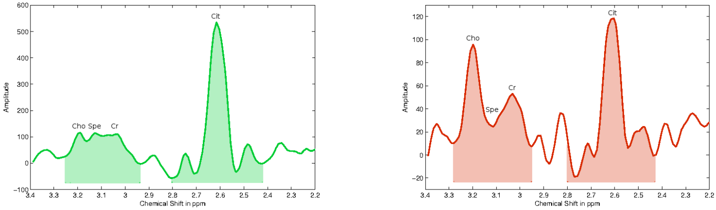
- Information about tissue structure
- ADC correlated with Gleason score

Cons

- Poor spatial resolution
- Variability of the ADC coefficient

MRI modalities

MRSI



(a) Healthy (b) CaP

Healthy

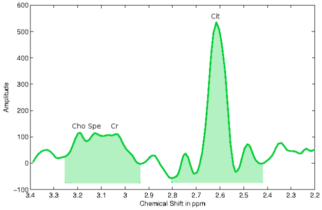
- High citrate
- Moderate choline and spermine

CaP

- Decrease of citrate and spermine
- Increase of choline

MRI modalities

MRSI



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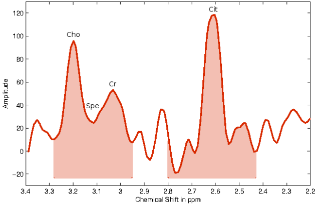


(d) CaP

Pros

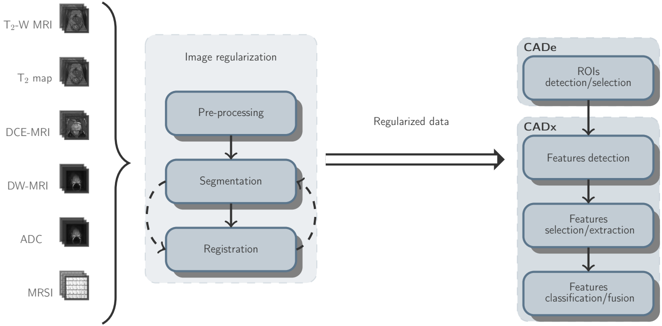
- Citrate correlated with Gleason score

Cons

- Low spatial resolution
- Variation inter-patients

CAD for CaP

Full CAD for detection and diagnosis of CaP

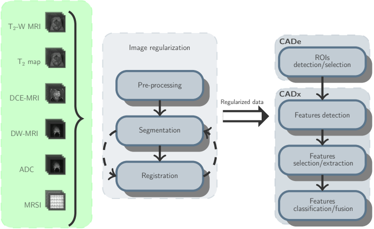


Common CAD framework based on MRI images used to detect CaP

CAD for CaP

Conclusions

- ✓ 3 modalities better than 2
- ✓ Texture and edge features are predominant
- ✓ Feature selection/extraction tends to improve performance
- ✓ Pre-eminence of SVM and ensemble classifier (i.e., AdaBoost, RF, etc.)



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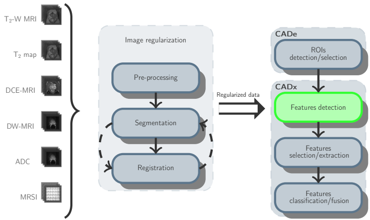

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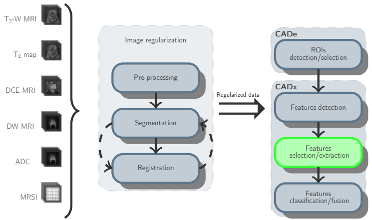

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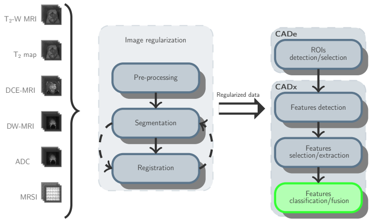

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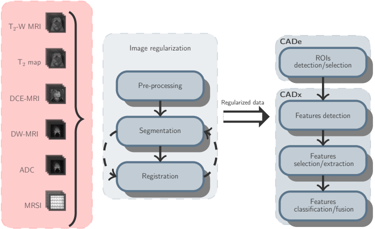
Scientific and technical challenges

- ✗ No publicly available mp-MRI dataset
- ✗ Only 1 study used 4 MRI modalities
- ✗ Limited work on data normalization
- ✗ A lot of features are extracted in 2D
- ✗ Limited work regarding selection/extraction
- ✗ No work regarding data balancing
- ✗ No source code available of any CAD

CAD for CaP



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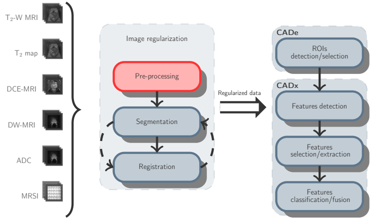

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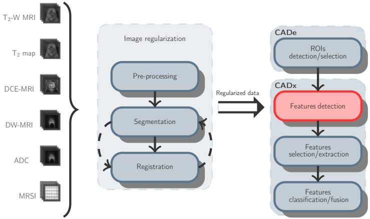

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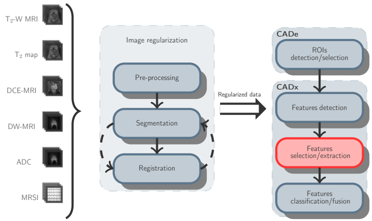

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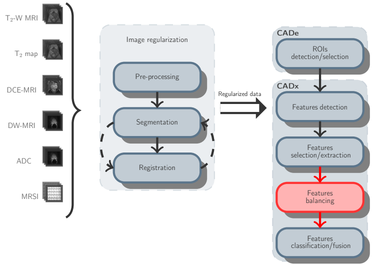

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Research objectives

- Collect a mp-MRI dataset
- Design a CAD for CaP using all mp-MRI modalities
- Investigate normalization, feature selection/extraction, data balancing
- Implement 3D features
- Release source code and dataset

1. Introduction
2. State-of-the-art
3. I2CVB
   - Mp-MRI prostate datasets
   - Overview

UdG

Mp-MRI prostate datasets

UBFC

1.5 T General Electric scanner

- T_2W-MRI, DW-MRI, DCE-MRI, and MRSI
- Ground-truth (GT) for CaP, PZ, and CG associated to T_2W-MRI modality
- Healthy: 4 *vs.* CaP: { PZ: $14 + 3$, CG: $0 + 3$ }

3 T Siemens scanner

- T_2W-MRI, ADC, DCE-MRI, and MRSI
- GT for CaP, PZ, and CG associated to T_2W-MRI modality
- Additional GT of the prostate for DCE-MRI and ADC
- Healthy: 2 *vs.* CaP: { PZ: $12 + 2$, CG: $3 + 2$ }

Mp-MRI prostate datasets

1.5 T General Electric scanner

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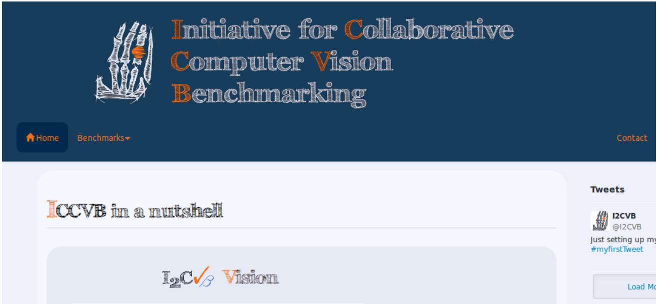
Overview

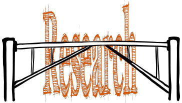
I2CVB Platform



- Development of a web platform

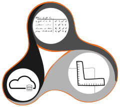
Manifesto

I2CVB Vision



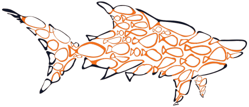
- Democratization of the ability to research

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