

# Computer-Aided Diagnosis for Prostate Cancer using mp-MRI

PhD Defence  
28<sup>th</sup> November 2016

Guillaume Lemaître

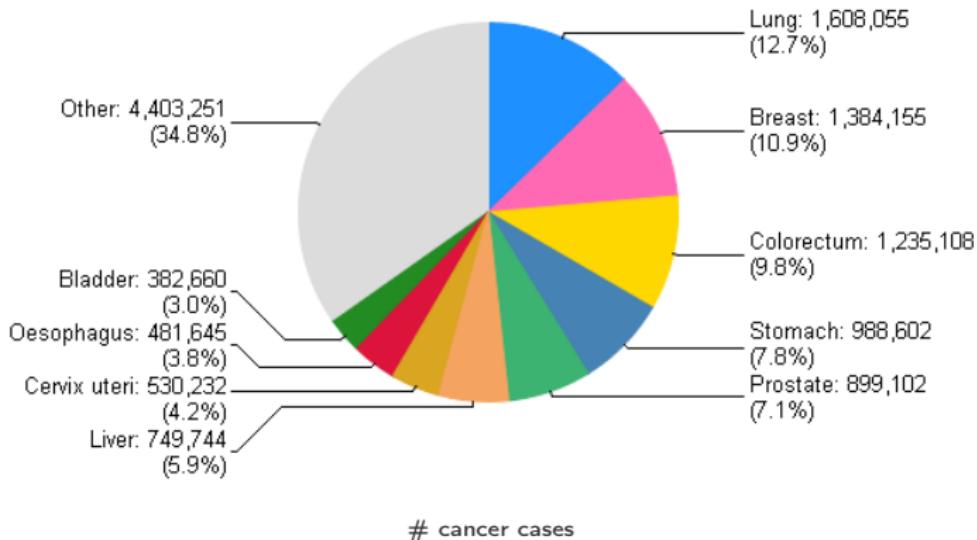
*Universitat de Girona - ViCOROB  
Université de Bourgogne Franche-Comté - LE2I*

Supervised by:

Robert Martí - Fabrice Mériauveau  
Jordi Freixenet - Paul M. Walker



## Statistics<sup>1</sup>



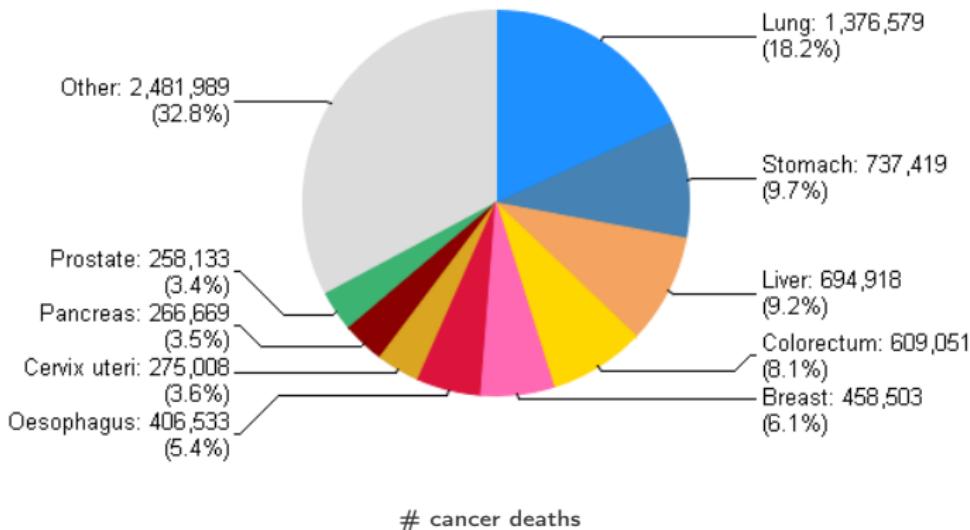
<sup>1</sup>J. Ferlay et al. "Estimates of worldwide burden of cancer in 2008: GLOBOCAN 2008". In: *Int. J. Cancer* 127.12 (Dec. 2010), pp. 2893–2917.



## Motivations



## Statistics<sup>1</sup>



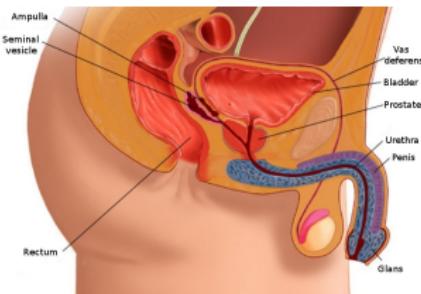
<sup>1</sup>Ferlay et al., "Estimates of worldwide burden of cancer in 2008: GLOBOCAN 2008".



## The prostate organ



Anatomy



Localization of the prostate organ, image source<sup>2</sup>

## Characteristics

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

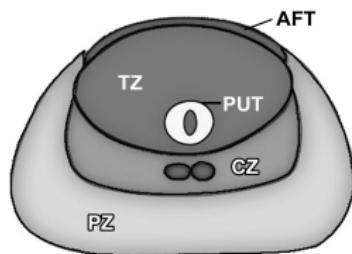
<sup>2</sup>Geckomedia. *Natom Anatomy*. French. June 2011. url: <http://www.natomshop.com/>.



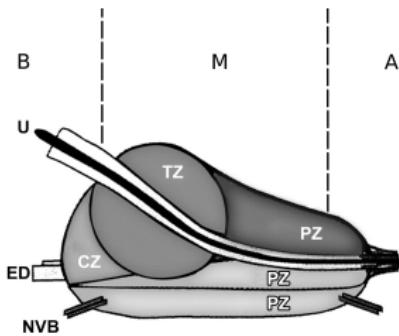
## The prostate organ



Anatomy



(a) Transverse plane



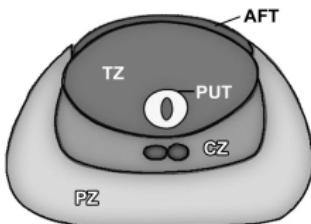
(b) Sagittal plane

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<sup>3</sup>

<sup>3</sup>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 (TZ+CZ) are more aggressive

## Zonal predisposition

- ▶ PZ → 70 % to 80 %
  - ▶ TZ → 10 % to 20 %
  - ▶ CZ → 5 %

## What clinicians need?

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

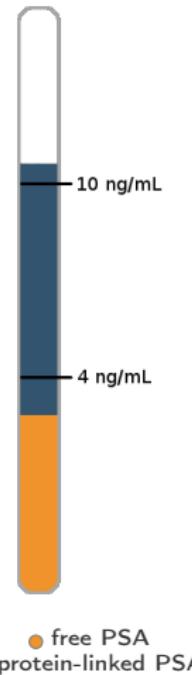


# Screening



## Prostate-specific antigen

- ▶  $> 10 \text{ ng mL}^{-1}$  → biopsy
- ▶ From  $4 \text{ ng mL}^{-1}$  to  $10 \text{ ng mL}^{-1}$   
 $\rightarrow \frac{\bullet}{\bullet + \bullet} > 15\% \rightarrow \text{biopsy}$



## "Blind" transrectal ultrasound biopsy

- ▶ Take samples from different locations
- ▶ Grade using Gleason score

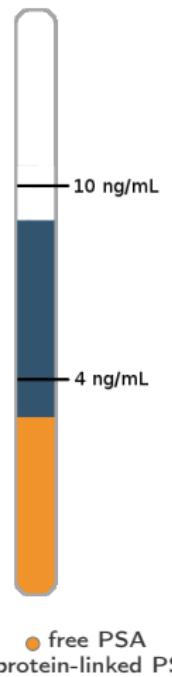


# Screening



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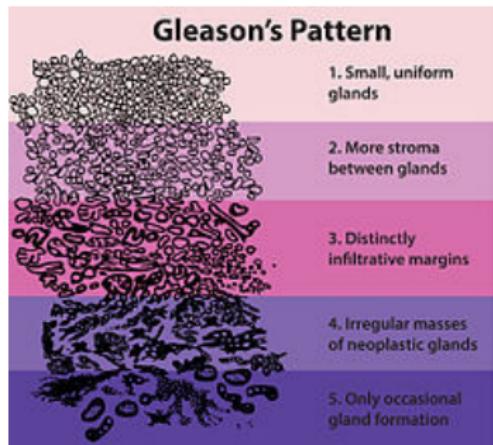


Image source: <https://goo.gl/fEVQXQ>



# Screening



## Pros

- ✓ Reduce CaP-related mortality between 21 % and 44 %<sup>4</sup>

## Cons

- ✗ Up to 30 % of over-diagnosis<sup>5</sup>
- ✗ Up to 35 % of undiagnosed CaP<sup>6</sup>
- ✗ Biopsies are invasive

<sup>4</sup>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.

<sup>5</sup>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.

<sup>6</sup>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



## Research objectives



### Propose a mp-MRI CAD for CaP

- ▶ Study and investigate the state-of-the-art on mp-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

## 4 Toward a mp-MRI CAD for CaP

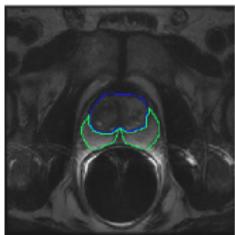
## 5 Conclusions



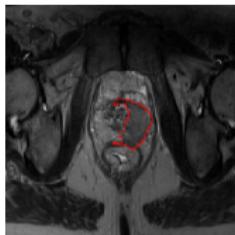
# MRI modalities



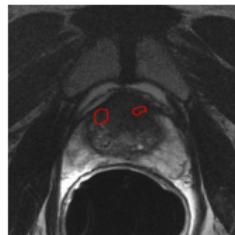
## T<sub>2</sub>W-MRI



(a) Healthy



(b) CaP PZ



(c) CaP CG

## Healthy vs. CaP

- ▶ Lower SI
- ▶ Ill-defined edges

## Pros and cons

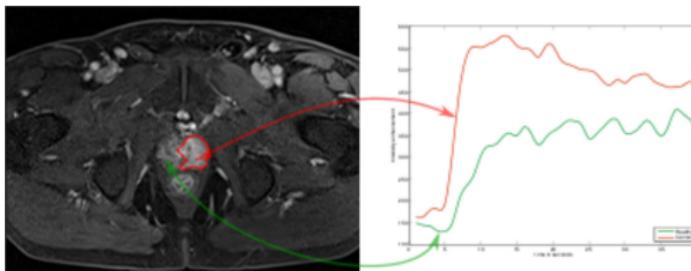
- ✓ High resolution
- ✓ Anatomy well depicted
- ✗ Low sensitivity in CG
- ✗ Lower specificity due to outliers



# MRI modalities



## DCE-MRI



Green: healthy - Red: CaP

## Healthy vs. CaP

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

## Pros and cons

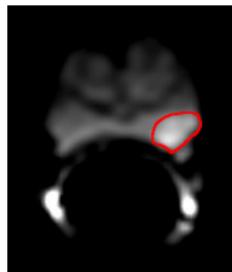
- ✓ Information about vascularity
- ✗ Spatial mis-registration
- ✗ Lower spatial resolution
- ✗ Difficult detection in CG
- ✗ Curve variations among patients



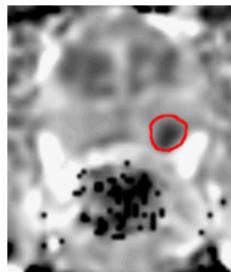
# MRI modalities



## DW-MRI - ADC



(a) DW MRI



(b) ADC

## Healthy vs. CaP

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

## Pros and cons

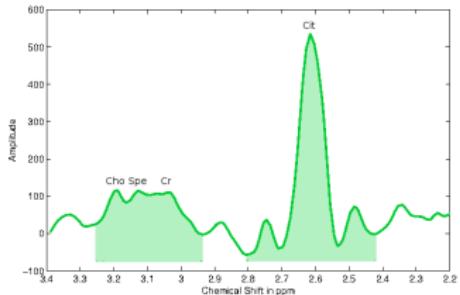
- ✓ Information about tissue structure
- ✓ ADC correlated with Gleason score
- ✗ Poor spatial resolution
- ✗ Variability of the ADC coefficient



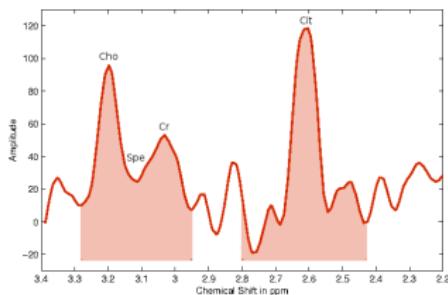
# MRI modalities



## MRSI



(a) Healthy



(b) CaP

## Healthy vs. CaP

- Decrease of citrate and spermine concentrations
- Increase of choline concentration

## Pros and cons

- ✓ Citrate correlated with Gleason score
- ✗ Low spatial resolution
- ✗ Variation inter-patients

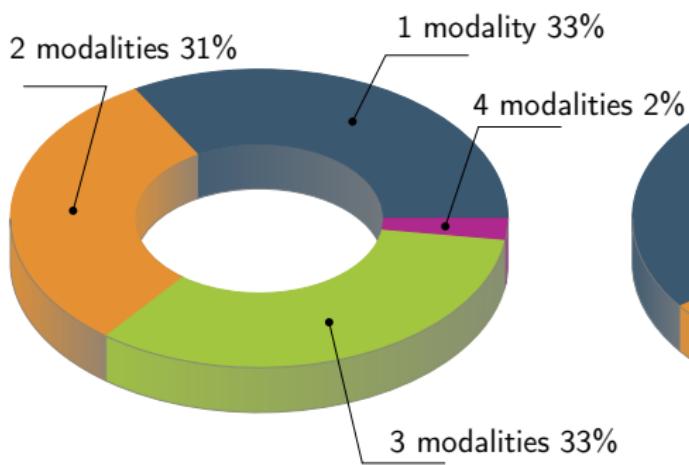


## CAD for Cap

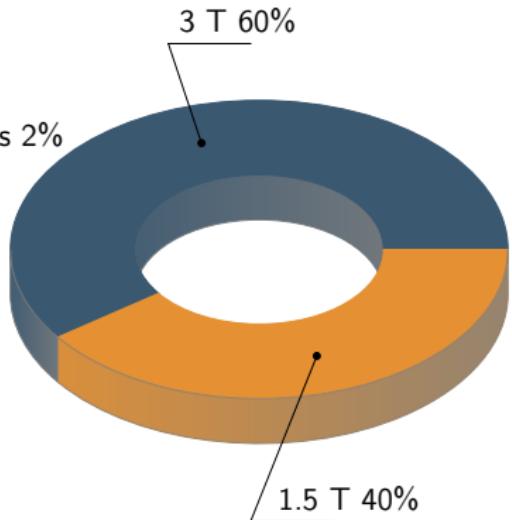


56 Studies

MRI modalities



MRI scanners



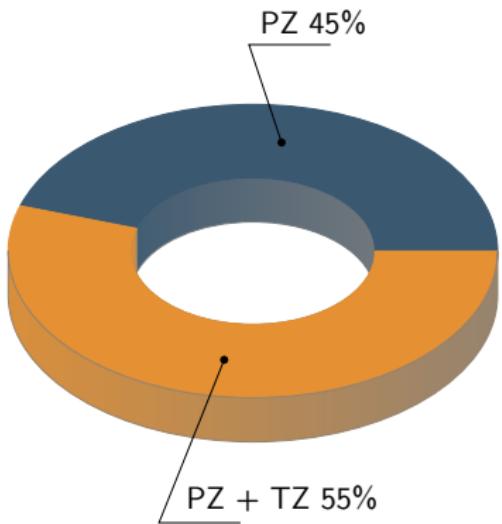


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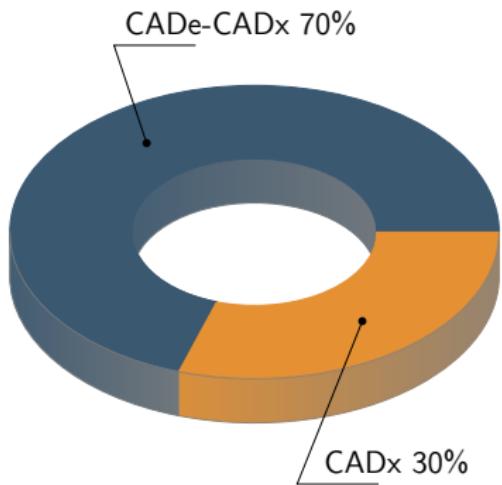


56 Studies

Zones studied



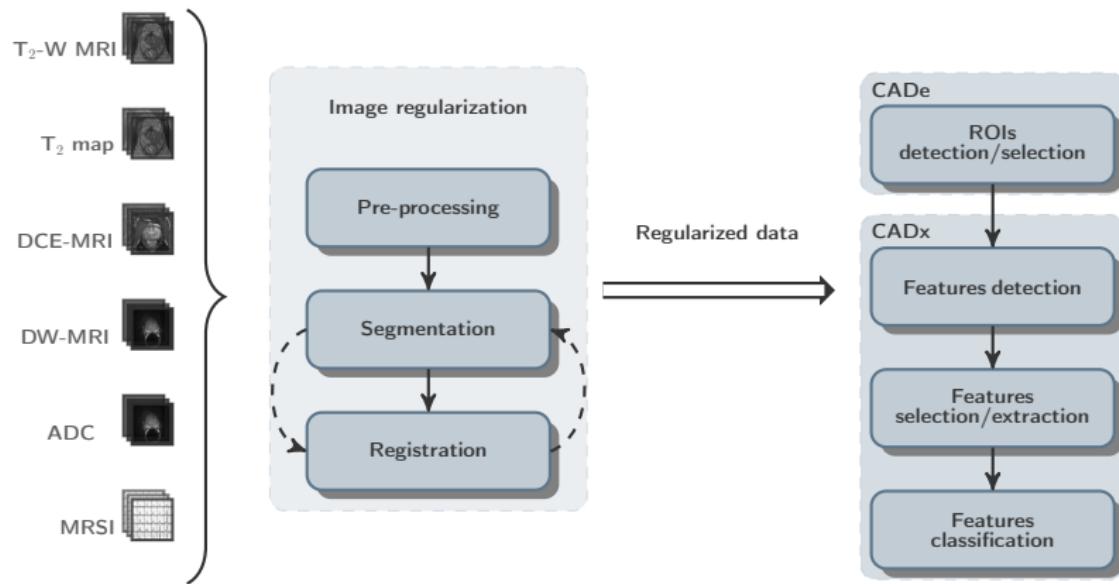
CAD types





# CAD for CaP

## Full CAD for detection and diagnosis of CaP



Common CAD framework based on MRI images used to detect CaP

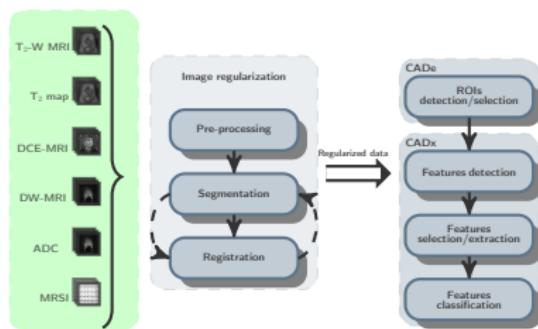


# CAD for CaP



## Conclusions

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



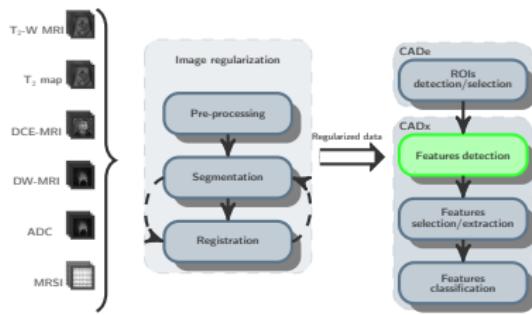


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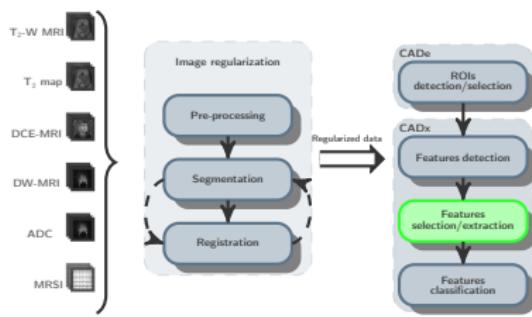


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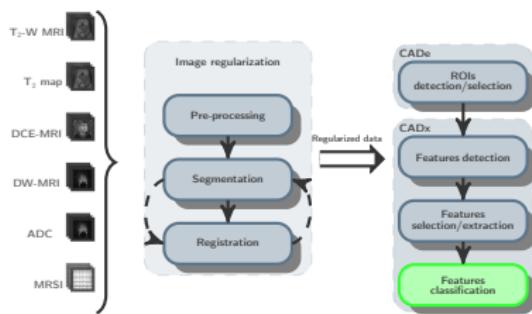


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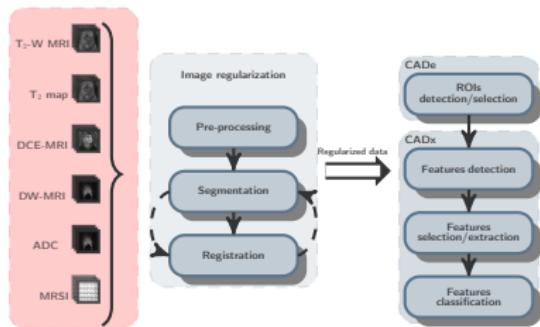
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## Scientific and technical challenges

- ✗ 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



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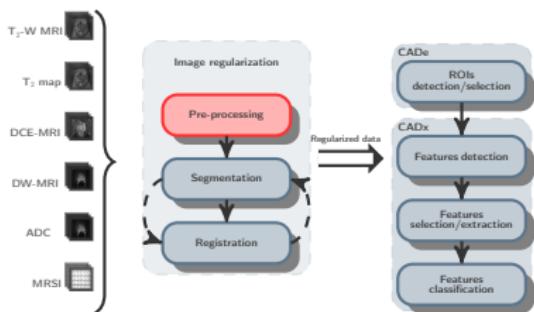


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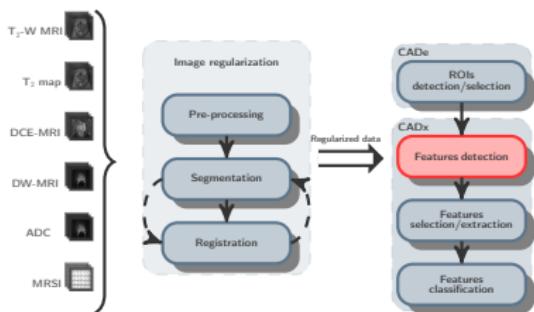


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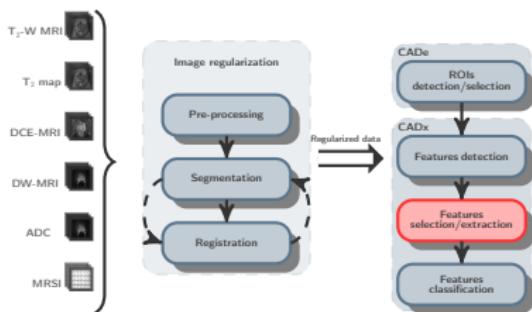


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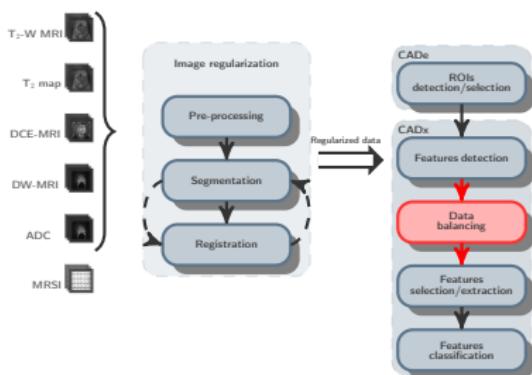


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## Research objectives

- ▶ 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
- Open source initiative
- I2CVB

## 4 Toward a mp-MRI CAD for CaP

## 5 Conclusions



# Mp-MRI prostate datasets



## 1.5 T General Electric scanner

- ▶ T<sub>2</sub>W-MRI, DW-MRI, DCE-MRI, and MRSI
- ▶ Ground-truth (GT) for CaP, PZ, and CG associated to T<sub>2</sub>W-MRI modality
- ▶ Healthy: 4 vs. CaP: { PZ: 14 + 3, CG: 0 + 3 }

## 3 T Siemens scanner

- ▶ T<sub>2</sub>W-MRI, ADC, DCE-MRI, and MRSI
- ▶ GT for CaP, PZ, and CG associated to T<sub>2</sub>W-MRI modality
- ▶ Additional GT of the prostate for DCE-MRI and ADC
- ▶ Healthy: 2 vs. CaP: { PZ: 12 + 2, CG: 3 + 2 }



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# Open source initiative



## protoclass toolbox

- ▶ Data management
- ▶ Features detection

## imbalanced-learn toolbox<sup>7</sup>

- ▶ Part of the scikit-learn-contrib projects

## Third-party toolboxes



<sup>7</sup>Guillaume Lemaître et al. "Imbalanced-learn: A Python Toolbox to Tackle the Curse of Imbalanced Datasets in Machine Learning". In: *Journal of Machine Learning Research* (2017).



# A web platform



## I<sub>2</sub>C<sub>V</sub>B platform

Initiative for Collaborative Computer Vision Benchmarking

Home Benchmarks Contact

ICCVB in a nutshell

I<sub>2</sub>C<sub>V</sub>B Vision

Tweets

I2CVB @I2CVB Just setting up my #myfirstTweet

## Hub for our different resources

- ▶ GitHub for our source codes
- ▶ Zenodo for our datasets
- ▶ HAL, arXiv, ResearchGate for our publications

1 Introduction

2 State-of-the-art

3 I2CVB

4 Toward a mp-MRI CAD for CaP

Image regularization  
CADe-CADx

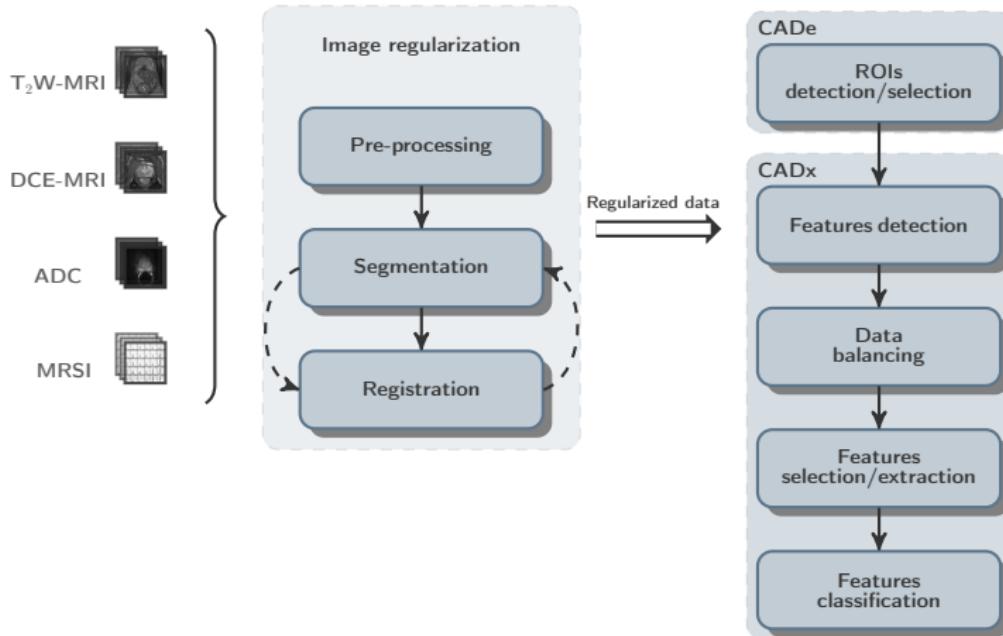
5 Conclusions



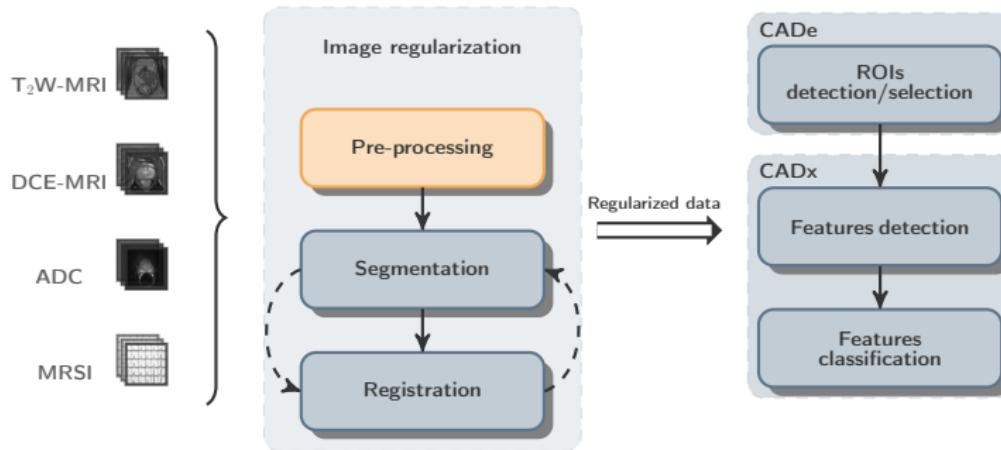
# Toward a mp-MRI CAD for CaP



## Mp-MRI CAD for CaP



## Pre-processing





# Pre-processing



## T<sub>2</sub>W-MRI normalization

- ▶ Rician normalization<sup>8</sup>

## DCE-MRI normalization

- ▶ Graph and deviation based normalization<sup>9</sup>

## ADC normalization

- ▶ Piecewise-linear normalization

## MRSI normalization

- ▶ Phase correction<sup>10</sup>
- ▶ Frequency alignment
- ▶ Baseline correction<sup>11</sup>

<sup>8</sup>Guillaume Lemaître et al. "Automatic prostate cancer detection through DCE-MRI images: all you need is a good normalization". In: *Medical Image Analysis - Submitted* (2017).

<sup>10</sup>Guillaume Lemaître et al. "Normalization of T2W-MRI Prostate Images using Rician a priori". In: *SPIE Medical Imaging*. International Society for Optics and Photonics. 2016, pp. 978529–978529.

<sup>11</sup>Li Chen et al. "An efficient algorithm for automatic phase correction of {NMR} spectra based on entropy minimization ". In: *Journal of Magnetic Resonance* 158.1–2 (2002), pp. 164–168.

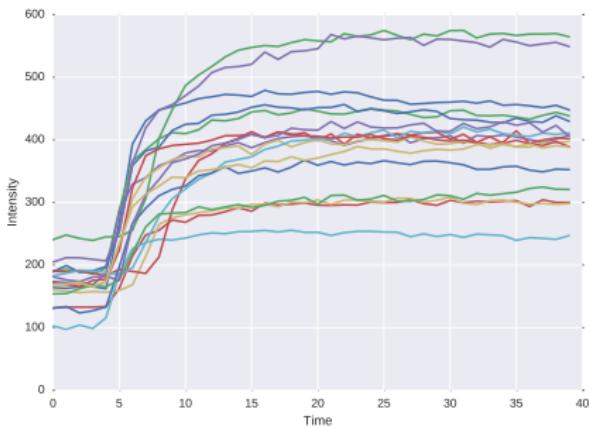
<sup>12</sup>Yuanxin Xi and David M Rocke. "Baseline correction for NMR spectroscopic metabolomics data analysis". In: *BMC bioinformatics* 9.1 (2008), p. 1.



# DCE-MRI normalization



## Inter-patients variations



## Contribution<sup>13</sup>

- ▶ Propose a method to normalize DCE-MRI data

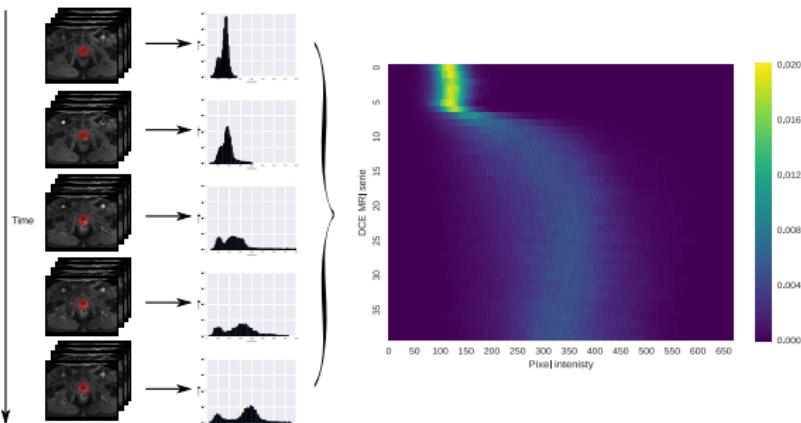
<sup>13</sup>Lemaître et al., "Automatic prostate cancer detection through DCE-MRI images: all you need is a good normalization".



# DCE-MRI normalization



## Heatmap representation



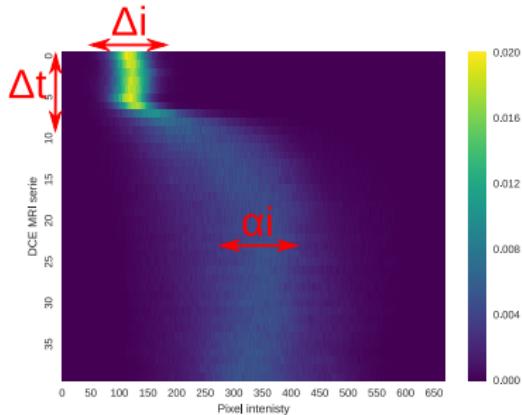
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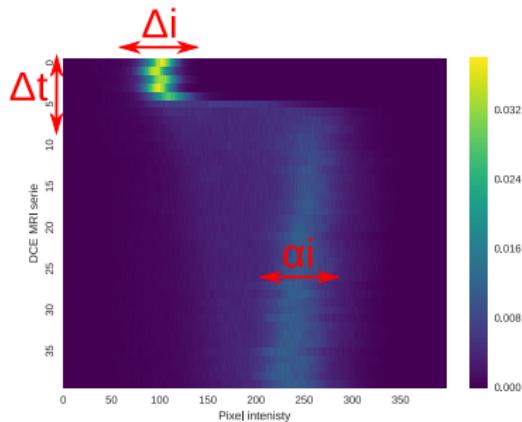
# DCE-MRI normalization



## Inter-patients variations



(a) Patient #1



(b) Patient #2

Variations driven by  $\Delta_i$ ,  $\Delta_t$ , and  $\alpha_i$



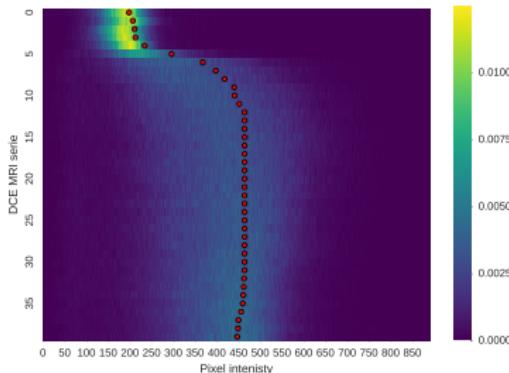
# DCE-MRI normalization



## Correction of $\Delta_i$

- ▶ Estimate with smooth transitions
- ▶ Estimate the closest of the PDF peak
- Find the shortest path in a directed weighted graph, with the edge weight  $w_{ij}$ :

$$w_{ij} = \begin{cases} \alpha \exp(1 - \frac{H(i)}{\max(H)}) & \text{if } x_j = x_i + 1 \text{ and } y_j = y_i, \\ (1 - \alpha) \exp(1 - \frac{H(i)}{\max(H)}) & \text{if } x_j = x_i \text{ and } y_j = y_i + 1, \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$





# DCE-MRI normalization

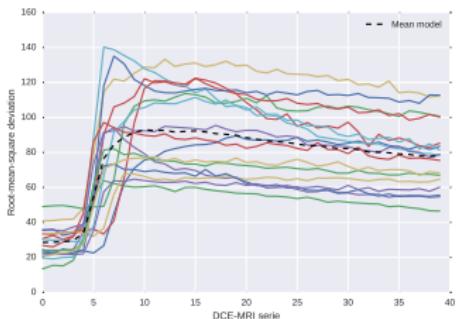
## Correction of $\Delta_t$ and $\alpha_i$

Register all RMSD to a mean model such that:

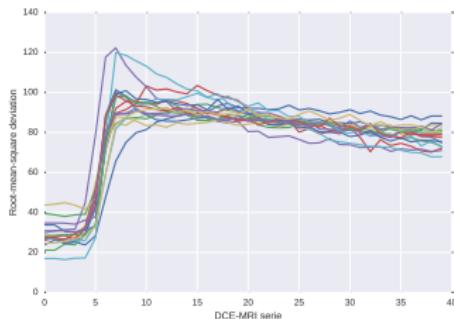
$$\arg \min_{\alpha, \tau} = \sum_{t=1}^N [T(\alpha, \tau, f(t)) - \mu(t)]^2, \quad (2)$$

$$f(t) = \sqrt{\left( \frac{\sum_{n=1}^N x(t)_n^2}{N} \right)}, \quad (3)$$

$$T(\alpha, \tau, f(t)) = \alpha f(t - \tau). \quad (4)$$



(a) RMSD before correction



(b) Registered RMSD



# DCE-MRI normalization



## Evaluation through pharmacokinetic models

- ▶ Brix's model
- ▶ Hoffmann's model
- ▶ Tofts' model
- ▶ PUN model

## Other approaches

- ▶ Semi-quantitative model
- ▶ Entire enhanced signal

## Classification

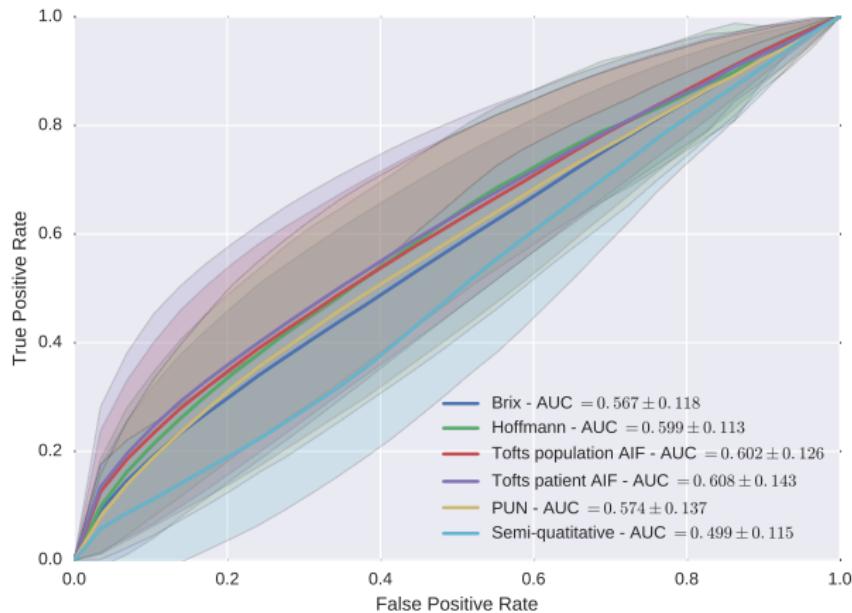
- ▶ Classification with random forest (RF)
- ▶ Leave-one-patient-out cross-validation (LOPO)
- ▶ Receiver operating characteristic (ROC) analysis
- ▶ Area under the ROC curve (AUC)



## DCE-MRI normalization



## Quantitative and semi-quantitative models

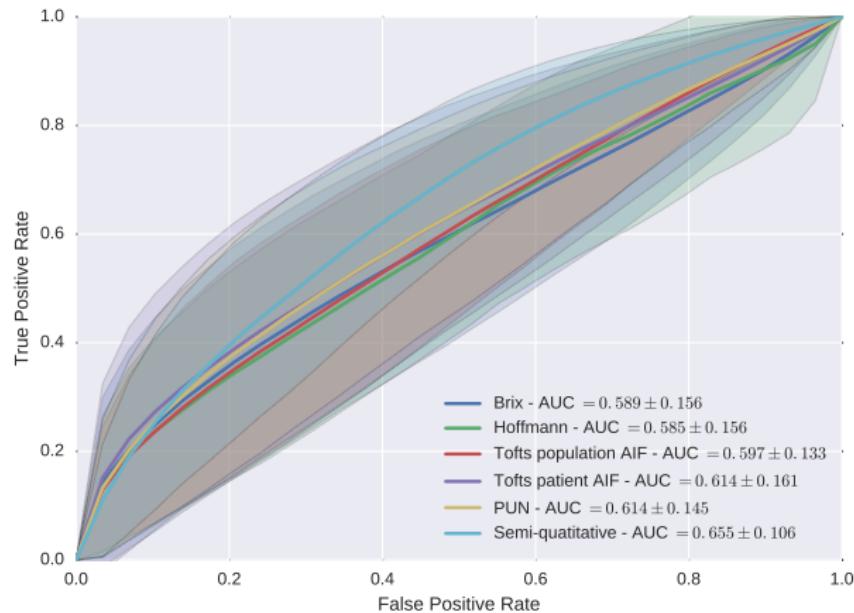


ROC analysis without normalization



# DCE-MRI normalization

## Quantitative and semi-quantitative models

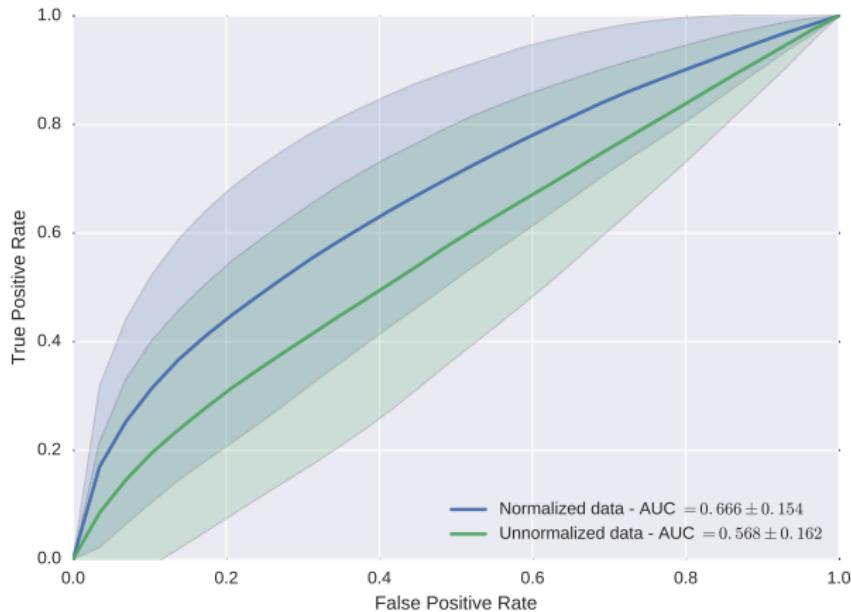


ROC analysis with normalization



# DCE-MRI normalization

Entire signal

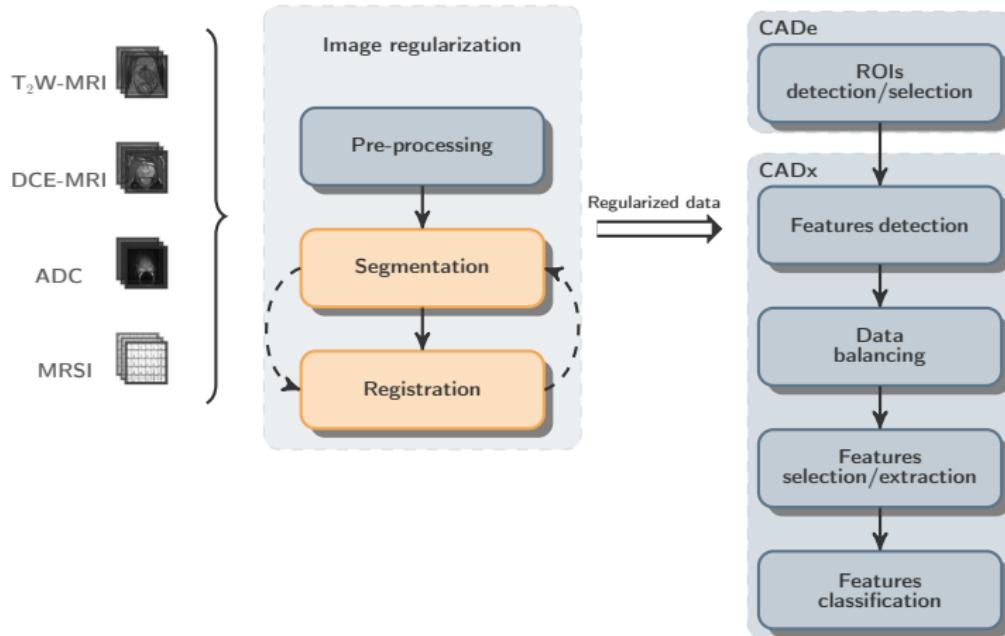


ROC analysis with entire enhanced signal



# Image regularization

## Segmentation & registration





# Segmentation & registration



## Resampling

- ▶ ADC and DCE-MRI are resampled to the T<sub>2</sub>W-MRI resolution

## Segmentation

- ▶ Manual prostate segmentation available for T<sub>2</sub>W-MRI, DCE-MRI, and ADC
- ▶ CaP, PZ, and CG manual segmentation available for T<sub>2</sub>W-MRI

## Registration

- ▶ Intra-patient motions correction in DCE-MRI: rigid registration using mutual information
- ▶ DCE-MRI is registered to T<sub>2</sub>W-MRI using the prostate segmentation
- ▶ ADC is registered to T<sub>2</sub>W-MRI using the prostate segmentation



## Summary of experiments

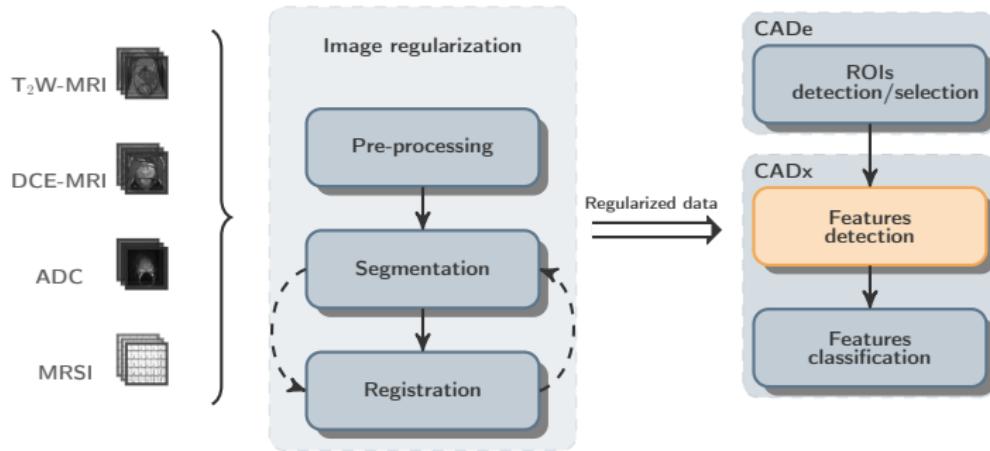
- ▶ Investigate the performance of features from each standalone modality
- ▶ Investigate the performance of the combination of features: *coarse combination*
- ▶ Investigate the effect of data balancing
- ▶ Investigate the effect of selection/extraction
- ▶ Investigate the performance of the combination of features: *fine-tuned combination*



## CADe-CADx



## Features detection





# Feature detection



## T<sub>2</sub>W-MRI and ADC features

- ▶ Intensity
- ▶ Kirsch filter
- ▶ Laplacian filter\*
- ▶ Prewitt filter\*
- ▶ Scharf filter\*
- ▶ Sobel filter\*
- ▶ DCT decomposition\*
- ▶ Gabor filters\*
- ▶ Phase congruency filter
- ▶ Haralick filter\*
- ▶ LBP filter\*

## DCE-MRI features

- ▶ Brix's model
- ▶ Hoffmann's model
- ▶ Tofts' model
- ▶ PUN model
- ▶ Semi-quantitative model
- ▶ Entire enhanced signal

## MRSI features

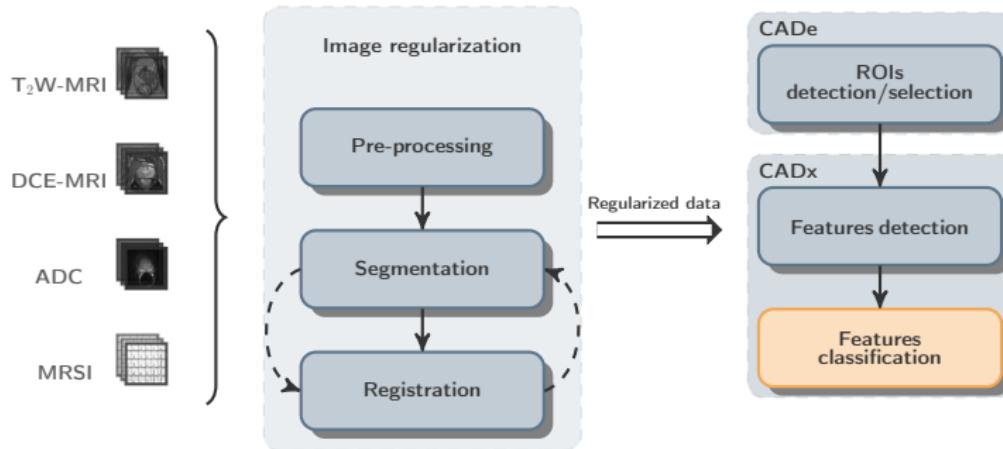
- ▶ Quantification with fixed bounds
- ▶ Quantification by fitting some modeled signal
- ▶ Entire spectra

## Spatial information

- ▶ Relative distance
- ▶ Relative position
- ▶ Prostate zone

\*These features are extracted using the 3D information

## Features classification



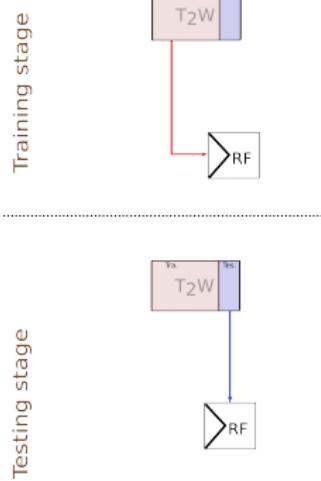


# Features classification



## Classification as fusion

- ▶ Single RF → features of one modality
- ▶ Single RF → aggregated features of modalities
- ▶ Stack of RF with an adaboost and gradient-boosting meta-classifier



## Validation

- ▶ LOPO CV
- ▶ ROC analysis
- ▶ AUC

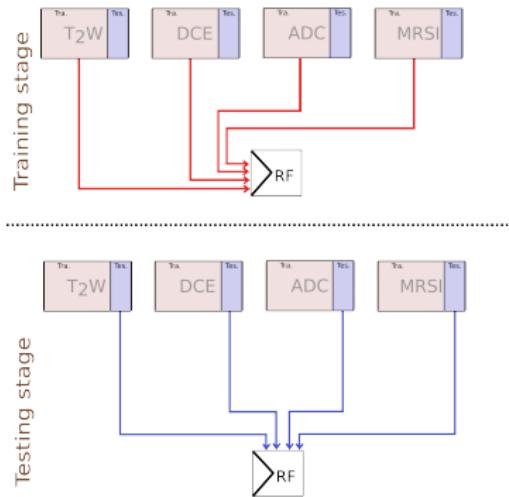


# Features classification



## Classification as fusion

- ▶ Single RF → features of one modality
- ▶ Single RF → aggregated features of modalities
- ▶ Stack of RF with an adaboost and gradient-boosting meta-classifier



## Validation

- ▶ LOPO CV
- ▶ ROC analysis
- ▶ AUC

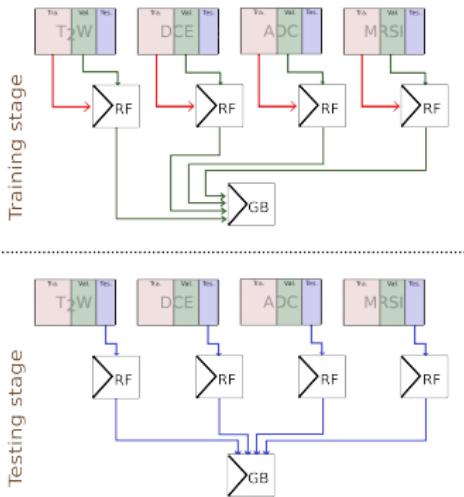


# Features classification



## Classification as fusion

- ▶ Single RF → features of one modality
- ▶ Single RF → aggregated features of modalities
- ▶ Stack of RF with an adaboost and gradient-boosting meta-classifier



## Validation

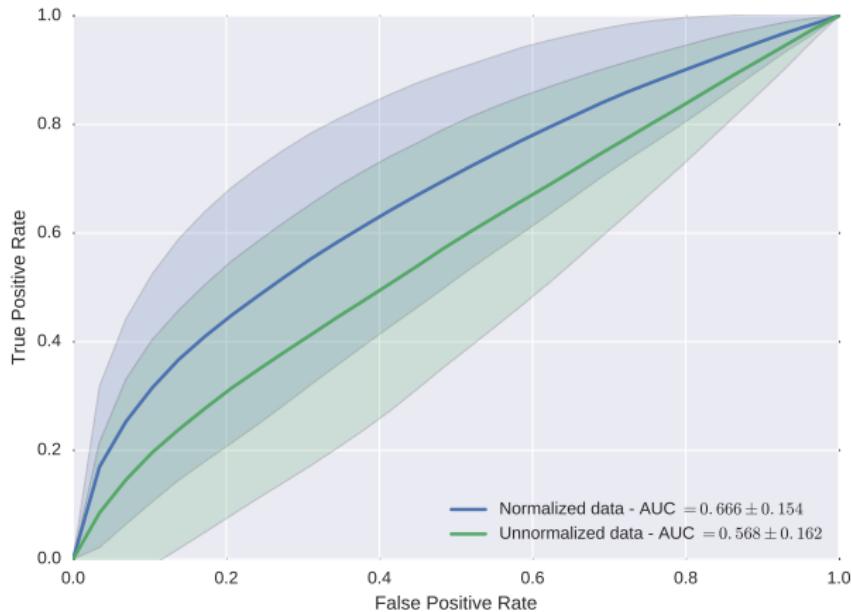
- ▶ LOPO CV
- ▶ ROC analysis
- ▶ AUC



## DCE modality



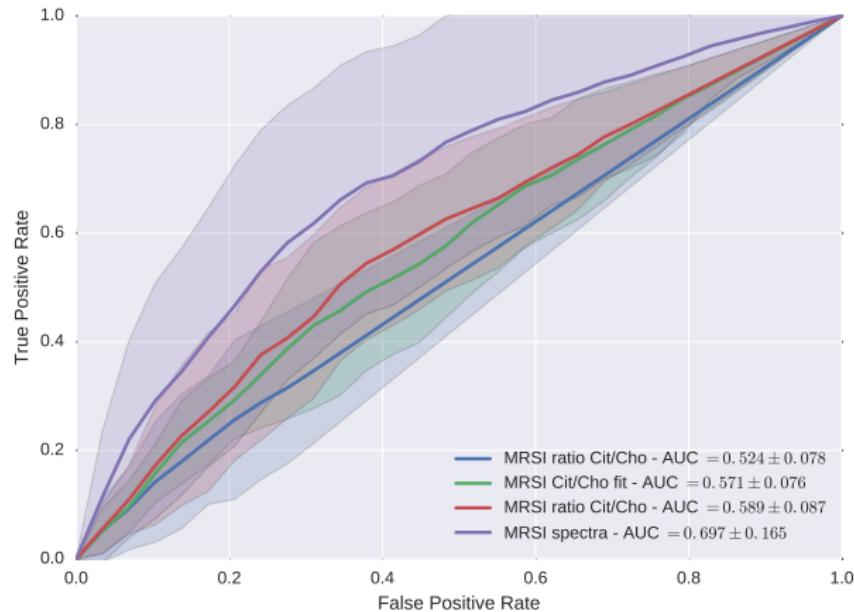
Entire signal



ROC analysis for the entire enhanced signal

## MRSI modalities

## ROC analysis

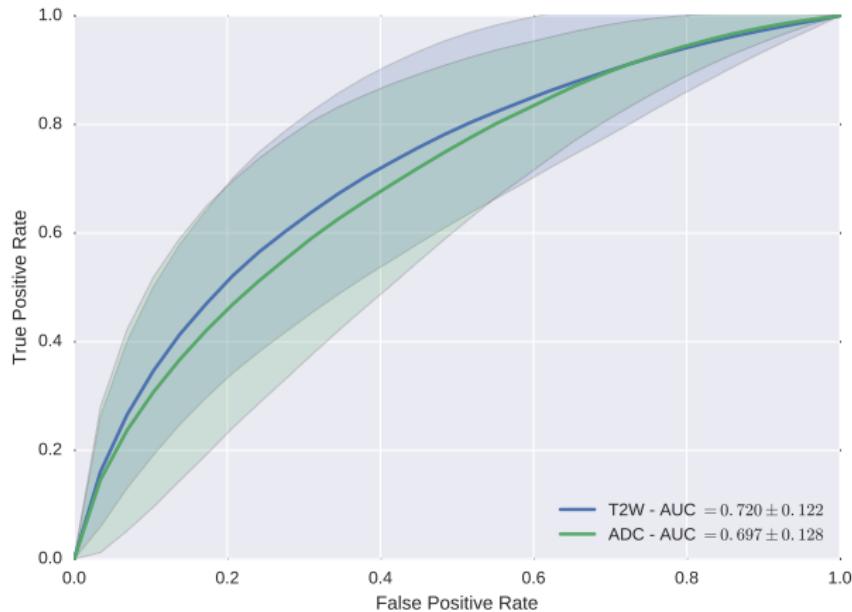


ROC analysis for the MRSI modality



# T<sub>2</sub>W-MRI and ADC

## ROC analysis



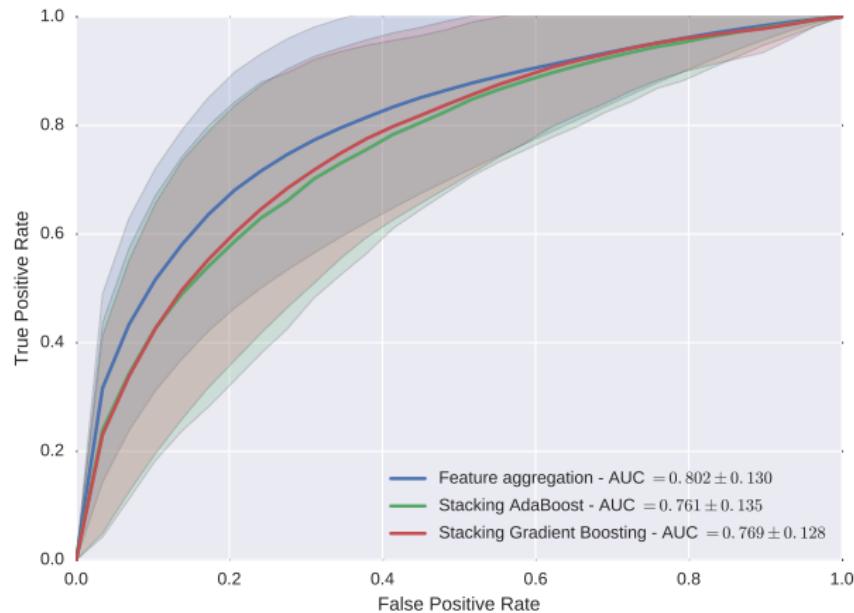
ROC analysis for T<sub>2</sub>W-MRI and ADC modalities



## Coarse combination



## Aggregation vs. stacking



ROC analysis for the fusion strategies



# Conclusions



## Overall best performance

AUC	T <sub>2</sub> W-MRI	DCE-MRI	ADC	MRSI	Aggregation
Mean	0.720	0.666	0.697	0.697	0.802
Std	0.122	0.154	0.128	0.165	0.130

## Conclusions

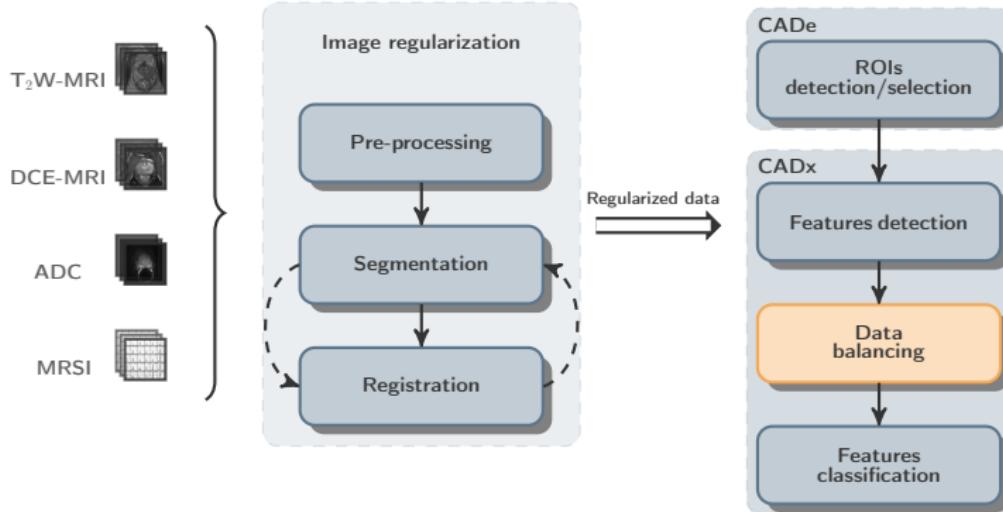
- ▶ DCE-MRI: normalized data → best performance
- ▶ DCE-MRI: entire signal better than models
- ▶ MRSI: fitting better than bounds approach
- ▶ MRSI: entire spectra better than others
- ▶ T<sub>2</sub>W-MRI > ADC = MRSI > DCE
- ▶ Performance at an “acceptable” level of discrimination - AUC ∈ [0.7, 0.8]
- ▶ Aggregation better than stacking



## CADe-CADx



## Data balancing

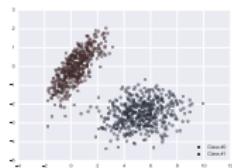




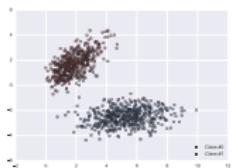
# Data balancing



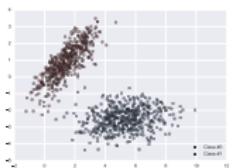
## Under-sampling



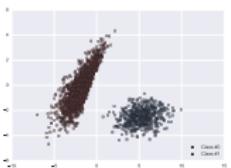
(a) NM1



(b) NM2

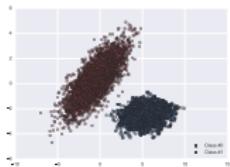


(c) NM3

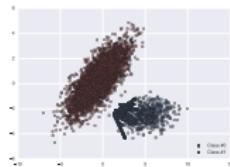


(d) IHT

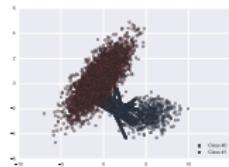
## Over-sampling



(e) SMOTE



(f) SMOTE-b1



(g) SMOTE-b2



# Data balancing



## Conclusions

- ✓ IHT → ADC and DCE-MRI
- ✓ SMOTE → T<sub>2</sub>W-MRI and MRSI
- ✓ NM3 → aggregate feature

## Before data balancing

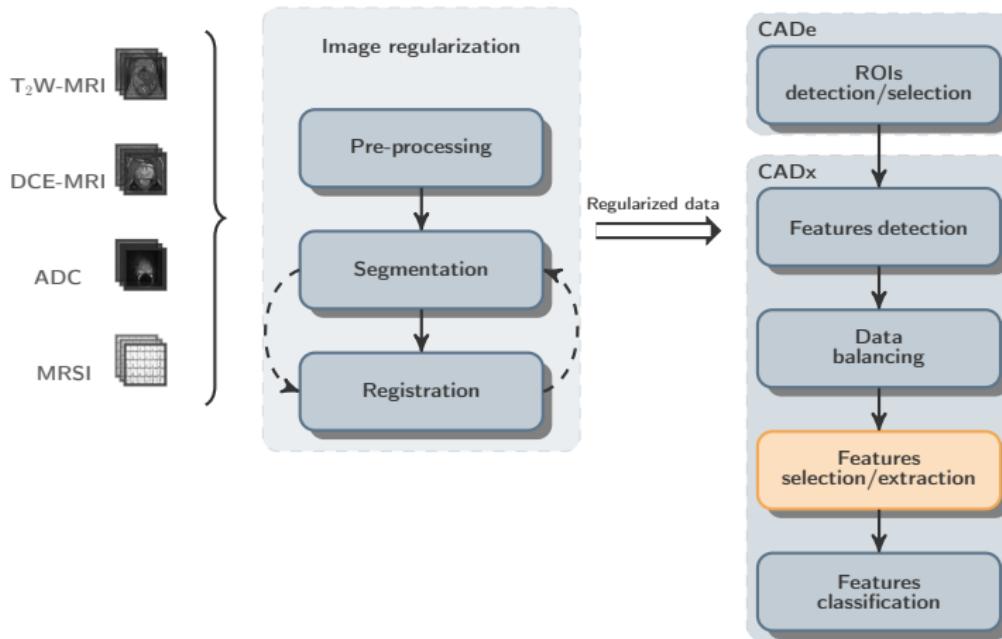
AUC	T <sub>2</sub> W-MRI	DCE-MRI	ADC	MRSI	Aggregation
Mean	0.720	0.666	0.697	0.697	0.802
Std	0.122	0.154	0.128	0.165	0.130

## After data balancing

AUC	T <sub>2</sub> W-MRI	DCE-MRI	ADC	MRSI	Aggregation
Mean	0.762	0.685	0.715	0.695	0.824
Std	0.081	0.145	0.142	0.156	0.076
Tendency	✓	✓	✓	=	✓



## Features selection/extraction





## Features selection/extraction



### Features extraction

- ▶ Independent components analysis (ICA)
- ▶ Principal components analysis (PCA)
- ▶ Sparse-PCA

### Features selection

- ▶ One-way analysis of variance (ANOVA)
- ▶ Gini importance



## Features selection/extraction



### Experiments

- ▶ Re-ordered feature depending on their importance
- ▶ Perform classification with different amount of features
- ▶ Find the threshold leading to the best classification performance

### Conclusions

- ✓ T<sub>2</sub>W-MRI: ANOVA-based selection with 25 % of features
- ✓ ADC: Gini importance-based selection with 5 % of features
- ✓ DCE-MRI: ICA with 24 components
- ✓ MRSI: ICA with 36 components
- ✓ Aggregation: Gini importance with 17.5 % of features



# Features selection/extraction



## Before features selection/extraction

AUC	T <sub>2</sub> W-MRI	DCE-MRI	ADC	MRSI	Aggregation
Mean	0.762	0.685	0.715	0.685	0.824
Std	0.081	0.145	0.142	0.156	0.076

## After features selection/extraction

AUC	T <sub>2</sub> W-MRI	DCE-MRI	ADC	MRSI	Aggregation
Mean	0.784	0.691	0.743	0.677	0.836
Std	0.067	0.158	0.139	0.171	0.083
Tendency	✓	✓	✓	✗	✓



## Features selection



### Selected features in T<sub>2</sub>W-MRI and ADC

T <sub>2</sub> W-MRI	ADC
8/12 edges	1/243 DCT
155/256 Gabor filters	32/256 Gabor filters
2/169 Haralick features	1/3 phase congruency
1/1 intensity	
4/6 LBP	
2/3 phase congruency	
172 features	34 features

### Selected features with aggregation

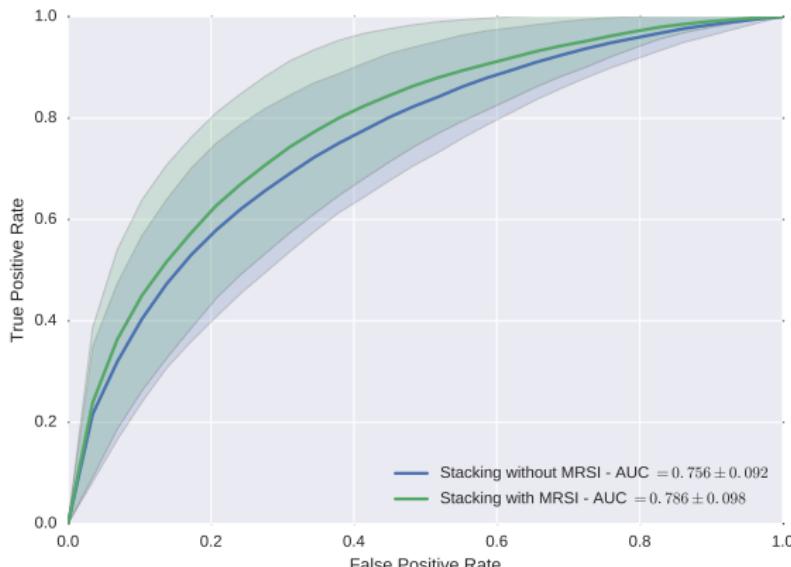
T <sub>2</sub> W-MRI	ADC	DCE-MRI	MRSI
113/256 Gabor filters 1/3 phase congruency 4/12 edges 1/1 intensity	53/256 Gabor filters 2/3 phase congruency	14/40 samples	78/101 samples
267 features			

# MRSI benefit

## Importance of MRSI in aggregation

- ▶ Features from MRSI are the most selected features

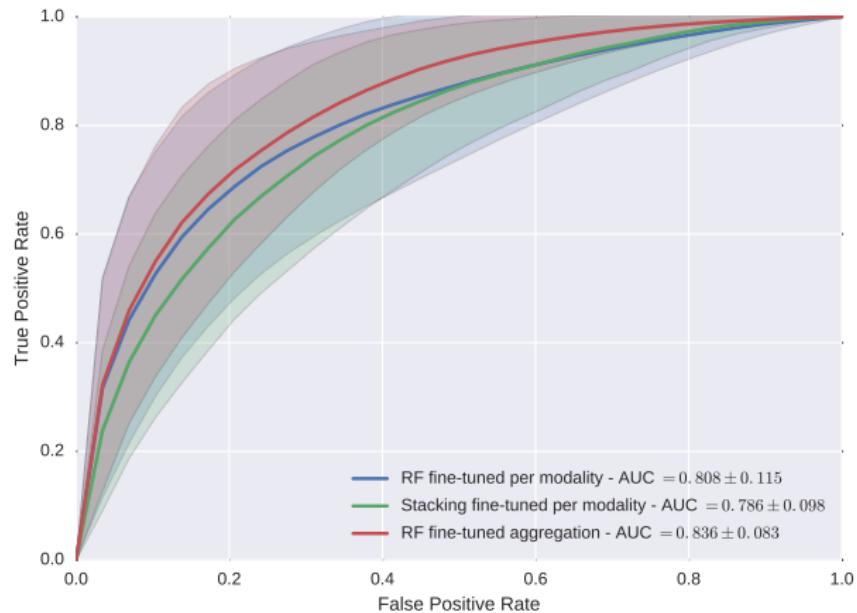
## Stacking with/without MRSI





# Fine-tuned combination

## Aggregation vs. stacking



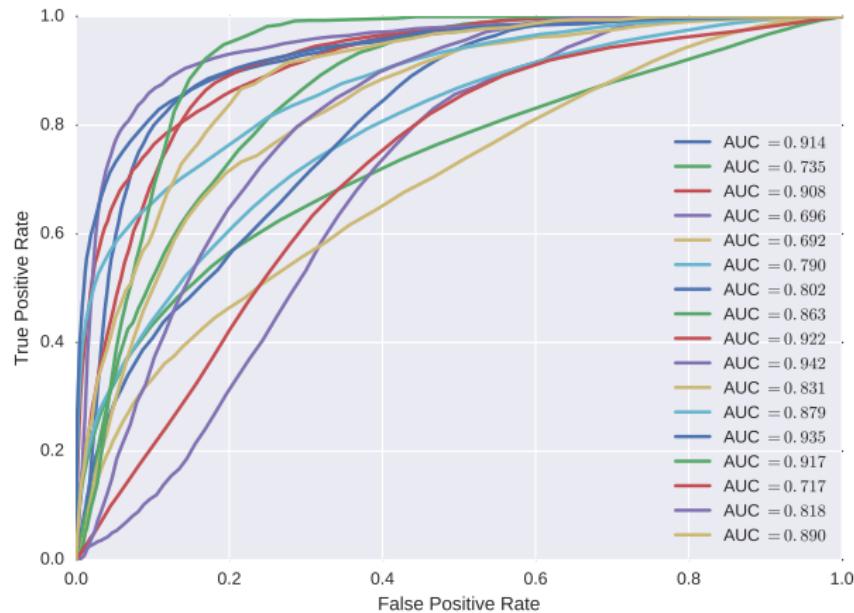
ROC analysis with the different fusion strategies



# Fine-tuned combination



## ROC for each patient

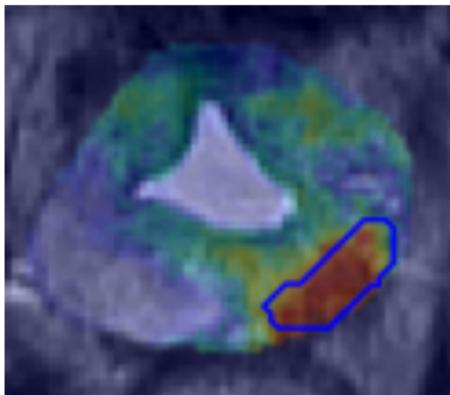




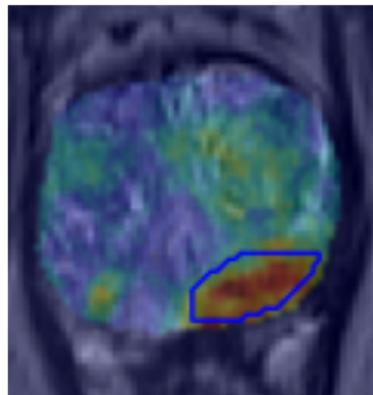
## Fine-tuned combination



“Outstanding” discrimination level



(a) AUC = 0.922



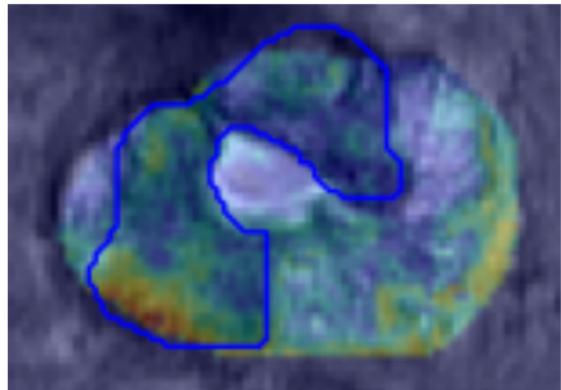
(b) AUC = 0.914



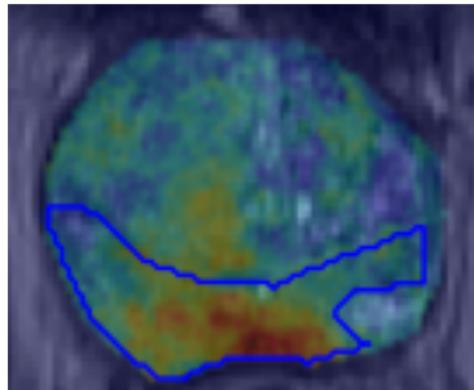
## Fine-tuned combination



“Acceptable” discrimination level



(c) AUC = 0.692



(d) AUC = 0.735

## 1 Introduction

## 2 State-of-the-art

## 3 I2CVB

## 4 Toward a mp-MRI CAD for CaP

## 5 Conclusions

Contributions & future works

Timeline



## Contributions & future works



### 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



## Contributions & future works



### Contributions

- ✓ Collect a mp-MRI dataset
- ✓ Design a CAD for CaP using all mp-MRI modalities
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# Contributions & future works



## Contributions

- ✓ 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

## Avenue for future research

- ✗ Incorporate spatial connectivity in classification using super-voxels
- ✗ Dissociate classifiers for the PZ and CG regions
- ✗ Explore the features from PI-RADS v.2
- ✗ Investigate the benefit of deep-learning



## Peer-Review Journals Papers

1. G. Lemaitre, R. Marti, M. Rastgoo, J. Massich, F. Freixenet, J. C. Vilanova, and F. Meriaudeau, "Automatic prostate cancer detection through DCE-MRI images: all you need is a good normalization", *Medical Image Analysis*, in Revision.
2. G. Lemaitre, F. Nogueira, and C. K. Aridas, "Imbalanced-learn: A Python Toolbox to Tackle the Curse of Imbalanced Datasets in Machine Learning", *Journal of Machine Learning Research*, vol. 17, (2017).
3. G. Lemaitre, R. Marti, J. Freixenet, J. C. Vilanova, P. M. Walker, and F. Meriaudeau, "Computer-Aided Detection and Diagnosis for prostate cancer based on mono and multi-parametric MRI: A Review", *Computer in Biology and Medicine*, vol. 60, pp 8 - 31, 2015.

## Peer-Review International Conferences

1. G. Lemaitre, M. Rastgoo, J. Massich, J. C. Vilanova, P. M. Walker, J. Freixenet, A. Meyer-Baese, F. Meriaudeau, and R. Marti, "Normalization of T2W-MRI prostate images using Rician a priori", *SPIE Medical Imaging 2016*. San Diego: USA (Feb. 2016).
2. G. Lemaitre, J. Massich, R. Marti, J. Freixenet, J. C. Vilanova, P. M. Walker, D. Sidibe, and F. Meriaudeau, "A Boosting Approach for Prostate Cancer Detection using Multi-parametric MRI", *International Conference on Quality Control and Artificial Vision (QCAV) 2015*. Le Creusot: France (Jun. 2015).



# Publications



## Peer-Review Journals Papers

1. D. Sidibe, S. Sankar, G. Lemaitre, M. Rastgoo, J. Massich, C. Y. Cheung, G. S. W. Tan, D. Milea, E. Lamoureux, T. Y. Wong, and F. Meriaudeau, "An anomaly detection approach for the identification of DME patients using SD-OCT images", *Medical Image Analysis, Computer Methods and Programs in Biomedicine*, vol. 139, pp 109 - 117, 2017.
2. G. Lemaitre, M. Rastgoo, J. Massich, C. Y. Cheung, T. Y. Wong, E. Lamoureux, D. Milea, F. Meriaudeau, and D. Sidibe, "Classification of SD-OCT Volumes using Local Binary Patterns: Experimental Validation for DME detection", *Journal of Ophthalmology*, vol. 2016, May 2016.
3. M. Belkacemi, C. Stolz, A. Mathieu, G. Lemaitre, J. Massich, and O. Aubretton, "Non destructive testing based on a scanning-from-heating approach: application to non-through defect detection and fiber orientation assessment", *Journal of Electronic Imaging*, vol. 24(6), pp 1- 8, November 2015.

## Peer-Review International Conferences

1. J. Massich, M. Rastgoo, G. Lemaitre, C. Cheung, T. Y. Wong, D. Sidibe, and F. Meriaudeau, "Classifying DME vs normal SD-OCT volumes: A review", *International Conference on Pattern Recognition*. Cancun: Mexico (Dec. 2016).
2. K. Alsaih, G. Lemaitre, J. Massich, M. Rastgoo, D. Sidibe, T. Y. Wong, E. Lamoureux, D. Milea, C. Leung, and F. Meriaudeau, "Classification of SD-OCT volumes with multi-pyramids, LBP, and HOG descriptors: Application to DME detection", *International Conference of the IEEE Engineering in Medicine and Biology Society*. Orlando: USA (Aug. 2016).



# Publications



## Peer-Review International Conferences

1. M. Rastgoo, G. Lemaitre, J. Massich, O. Morel, F. Marzani, R. Garcia, and F. Meriaudeau, "A study of data imbalancing for melanoma classification", *Bioimaging*. Rome: Italy (Feb. 2016).
2. M. Rastgoo, G. Lemaitre, O. Morel, J. Massich, F. Marzani, R. Garcia, and D Sidibe, "Classification of melanoma lesions using sparse coded features and random forests", *SPIE Medical Imaging*. San Diego: USA (Feb. 2016).
3. G. Lemaitre, M. Rastgoo, J. Massich, S. Sankar, F. Meriaudeau, and D. Sidibe, "Classification of SD-OCT volumes with LBP: Application to DME detection", *Ophthalmic Medical Image Analysis Workshop (OMIA), Medical Image Computing and Computer Assisted Interventions (MICCAI) 2015*. Munich: Germany (Oct. 2015).
4. G. Lemaitre, A. Bikfalvi, J. Llach, J. Massich, and F. Julian, "Business Model Design for University Technology Valorisation", *International Technology, Education and Development Conference (INTED) 2015*. Madrid: Spain (Mar. 2015).