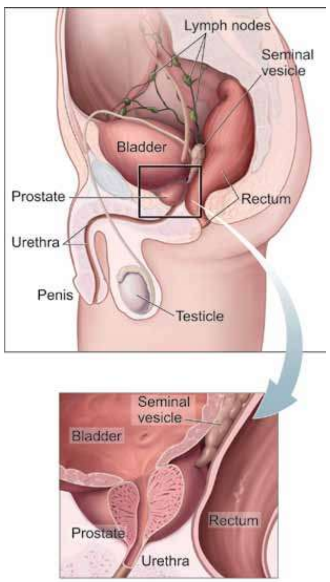
3D Segmentation and Registration for Minimal Invasive Prostate Cancer Therapy

WU Ke

Outlines

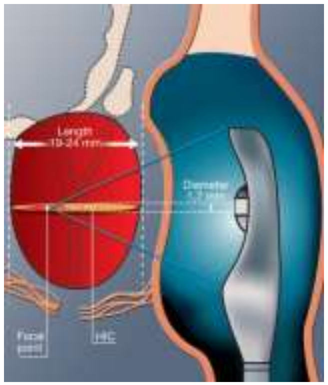
- Background of research
  - Prostate cancer and treatment
  - Ablatherm HIFU device and MULTIP Project
- Region Based Information Characterization in Ultrasound Image
  - Moment invariant based texture analysis in ultrasound image
    - Texture descriptor ability of moment invariant
    - Region and boundary information: graph cut on speckle image
- Feature based registration
  - OSD based prostate segmentation on T2 MRI
    - Single OSD based segmentation framework
    - Multiple objects OSD based segmentation framework
  - Surface-to-surface registration
    - Demons algorithm based registration
    - Evaluation on physical phantom and real data
- Conclusions

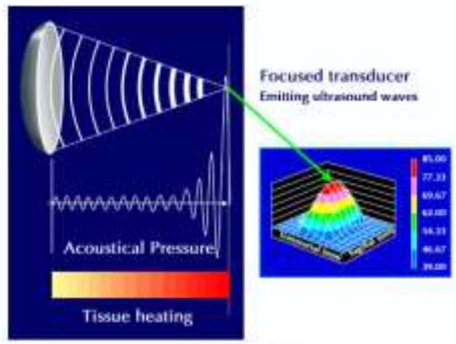
Prostate Cancer



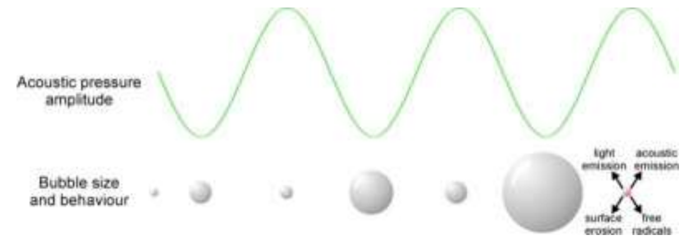
- Prostate anatomy
  - In front of rectum
  - Under bladder
  - Surrounds urethra
- Prostate cancer
  - Tumors in prostate (status T1-T4)
- Treatment
  - Radical surgery
  - Cryosurgery
  - Radiation therapy
  - High intensity focused ultrasound (HIFU)
  - Combination of treatments

High Intensity Focused Ultrasound





Focused ultrasound generating heat in a targeted area.



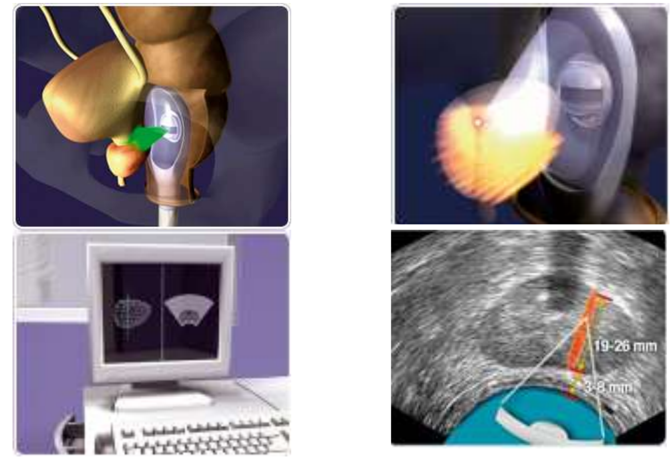
- Principle
  - Thermal effect
  - Cavitations
- Advantage
  - Noninvasive treatment
  - Treatment in one pass. Short hospital stay
  - Possibility of repeated procedure
  - Possibility of secondary radical treatment
  - Limited morbidity

Ablatherm HIFU Treatment

Ablatherm HIFU device

Mixed imaging and therapy probe

(http://www.edap-tms.com/)



- HIFU treatment
  - Intraoperative planning
    - Scan prostate with probe to get intraoperative transrectal ultrasound (TRUS) image
    - Plan the treatment and program the robot based on intraoperative TRUS image
  - Automated treatment
    - The probe generates a high intensity focused ultrasound beam to destroy lesion part of the prostate
    - The state of progress monitored by physician in real-time

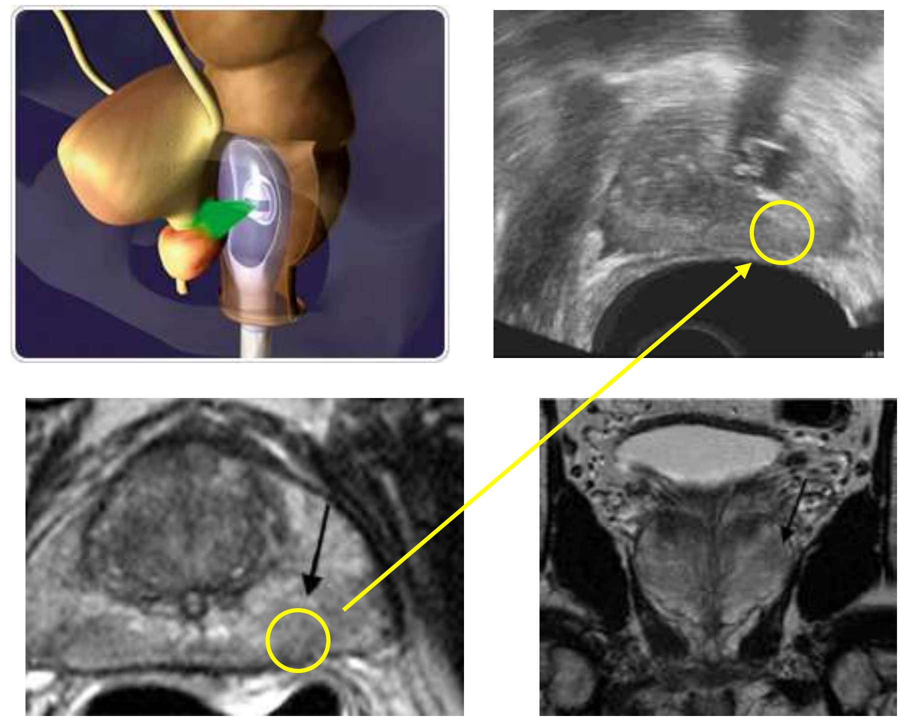
ANR TecSan MULTIP Project

- MULTIP Project
  - **M**atrice de transducteurs **U**ltrasonores pour **L**a **T**hérapie et **I**'Imagerie de la **P**rostate

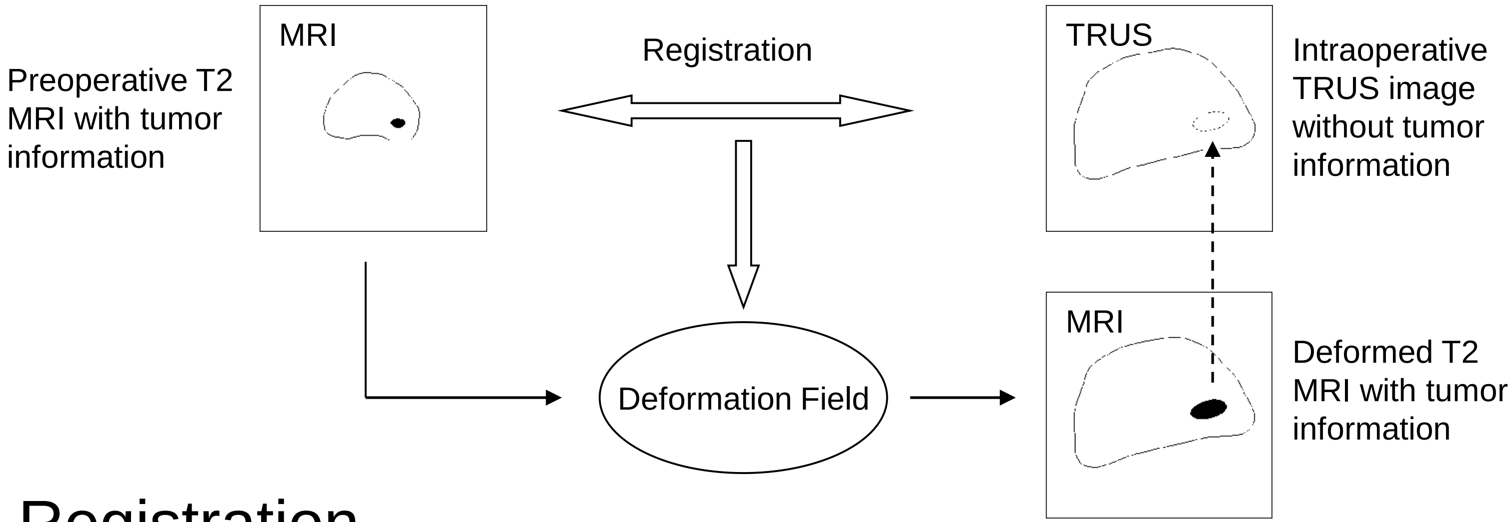
- Purpose
  - Development of a dual-mode probe
    - New geometry of multi-element probe
  - Imaging guided system for focal therapy

Imaging Guided Therapy Problem

- Intraoprative TRUS
  - Imaging transducer embedded to the probe
  - Scan and imaging the whole prostate gland in real-time
  - **No information about lesion**
- Preoperative T2 MRI
  - Performed 6–8 weeks after prostate biopsy
  - Provide spatially localized information
  - Locate the lesion in the prostate
- Solution
  - MR-TRUS registration to report lesion location to TRUS



MR-TRUS Registration



- Registration
  - Geometrical transformations
    - Global transformation: translation, rotation, scaling, affine …
    - Elastic transformation: spline, fluid flow …
  - Similarity measures
    - Intensity measures: <u>voxels intensities</u>
    - Feature measures: fiducial marks, lines, <u>surfaces</u> …
  - Optimization
    - Tuning transformation parameters to maximize similarity measure

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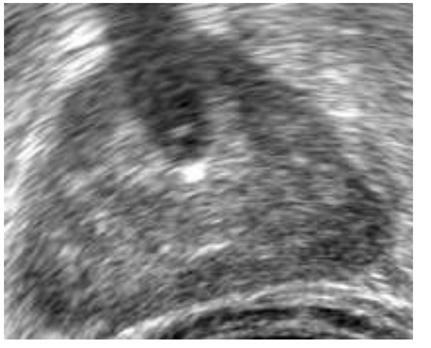
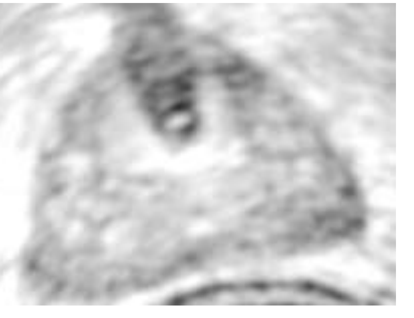
Intensity-based Registration

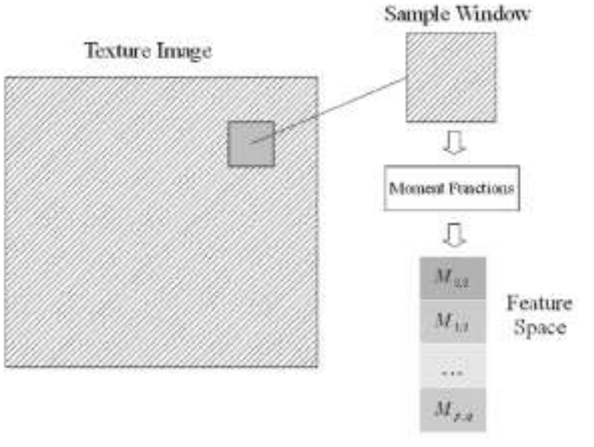
- Intensity-based registration
  - No previous feature extraction
  - Registration between different modalities
  - Relative robustness
- Problem in ultrasound images
  - Spatial speckle distribution but not a specific gray level distribution
- Solution
  - Consider speckle distribution as a kind of texture
  - Introduce a texture descriptor to convert speckle information to intensity information





Moment Invariant Based Texture Analysis

- Moments
  - Ability of texture characterization
    - Computing a set of moments on regions of interests (ROIs) of the texture images
- TRUS image
  - Size of the speckle increases according to distance to the probe
  - Speckle orientation depending on its position in the image
  - Texture descriptor should be invariant to rotation and scaling
- Moment invariants
  - Invariance against geometrical transformations (rotation, scaling …)



From Orthogonal Moments to Moment Invariants

- Zernike moment (*ZM*) of order *p* and repetition *q* of image intensity function $f(r,\theta)$ is defined as:

$$ZM_{p,q}^{f} = \frac{p+1}{\pi}\int_0^{2\pi}\int_0^1 R_{p,q}(r)e^{-jq\theta} f(r,\theta)rdrd\theta, \quad p \ge 0, \quad |q| \le p, \quad p-|q| \quad being \quad even$$

With $R_{p,q}(r)$ is the real-valued radial polynomial given by:

$$R_{p,q}(r) = \sum_{k=0}^{(p-|q|)/2} \frac{(-1)^k (p-k)!}{k!\left(\frac{p+|q|}{2}-k\right)!\left(\frac{p-|q|}{2}-k\right)!} r^{p-2k}$$

Magnitude of the Zernike moment should be invariant to rotation, but no scaling invariance

- A complete set of Zernike moment invariants (*ZMIs*) with respect to image rotation and scaling of order *p* and repetition *q* of an image intensity function $f(r,\theta)$ has been constructed as:

$$ZMI_{p=q+2m,q}^{f} = e^{-jq\theta_f} \sum_{k=0}^{m}\sum_{l=k}^{m} \Gamma_f^{-(q+2l+2)} c_{m,l}^{q} d_{l,k}^{q} ZM_{q+2k,q}^{f}$$

(Chen, Shu et al. 2011)

with $\theta_f = \arg\left(ZM_{1,1}^{f}\right)$, $\Gamma_f = \sqrt{ZM_{0,0}^{f}}$ and

Rotation invariant term

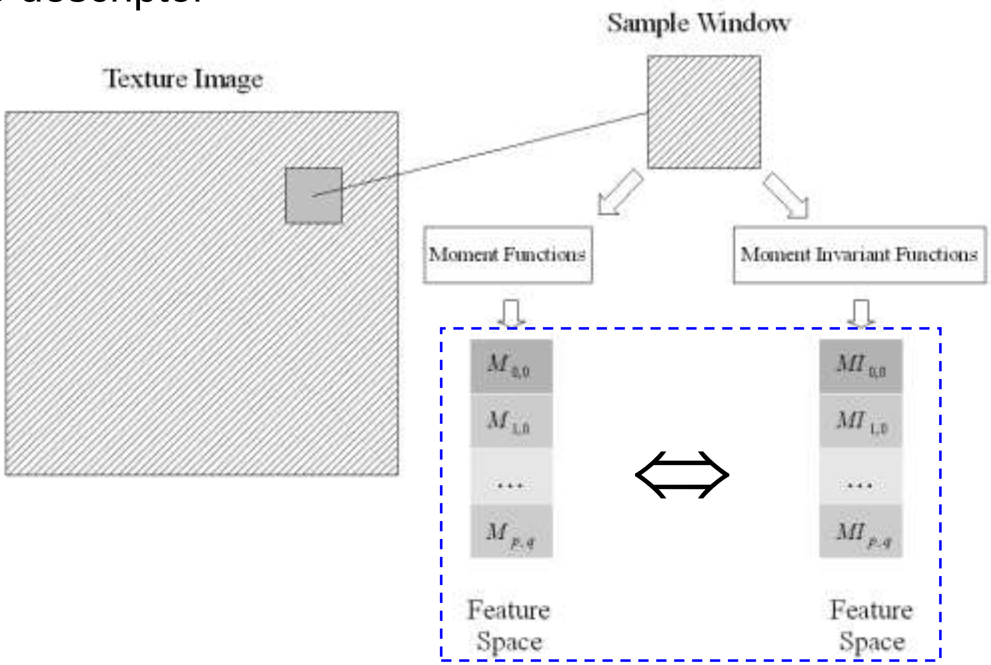
$$c_{m,l}^{q} = (-1)^{m-l}\frac{q+2m+1}{\pi}\frac{(q+m+l)!}{l!(m-l)!(q+l)!}$$

$$d_{l,k}^{q} = \pi\frac{l!(q+l)!}{(l-k)!(q+l+k+1)!}$$

Scaling invariant term

Moment Invariants as Texture Descriptor

- Texture descriptor



  - The complete sets of moment invariants are linear combinations of their original moments

$$\begin{pmatrix} ZMI^{f}_{q,q} \\ ZMI^{f}_{q+2,q} \\ \vdots \\ ZMI^{f}_{q+2m,q} \end{pmatrix} = e^{-jq\theta_f} C^{q}_{m} diag\left(\Gamma_f^{-(q+2)}, \quad \Gamma_f^{-(q+4)}, \quad \cdots \quad \Gamma_f^{-(q+2m+2)}\right) D^{q}_{m} \begin{pmatrix} ZM^{f}_{q,q} \\ ZM^{f}_{q+2,q} \\ \vdots \\ ZM^{f}_{q+2m,q} \end{pmatrix}$$

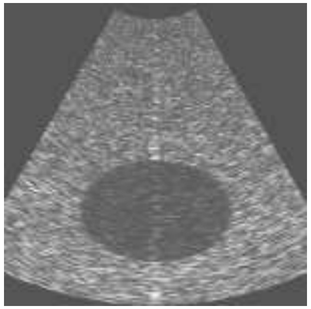
Evaluation of Invariance

- Rotation and scaling invariance
  - Theoretically proved
  - Evaluation on different materials
    - Brodatz texture images
    - Simulated ultrasound image
    - Real ultrasound image
  - Moment invariants
    - Zernike moment invariants (*ZMIs*) (Chen, Shu et al. 2011)
    - Pseudo-Zernike moment invariants (*PZMIs*) (Zhang, Dong et al. 2010)
    - Orthogonal Fourier-Mellin moment invariants (*OFMMIs*) (Zhang, Shu et al. 2010)

D4

D9

D17



Simulated ultrasound image

Real ultrasound image

Chen, B., et al. (2011). "Combined invariants to similarity transformation and to blur using orthogonal Zernike moments." Image Processing, IEEE Transactions on 20(2): 345-360.

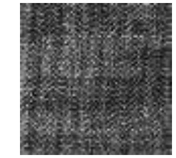
Zhang, H., et al. (2010). Object recognition by a complete set of pseudo-Zernike moment invariants. Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on, IEEE.

Zhang, H., et al. (2010). "Construction of a complete set of orthogonal Fourier–Mellin moment invariants for pattern recognition applications.“ Image and vision computing 28(1): 38-44.

Rotation Invariance: Brodatz Texture

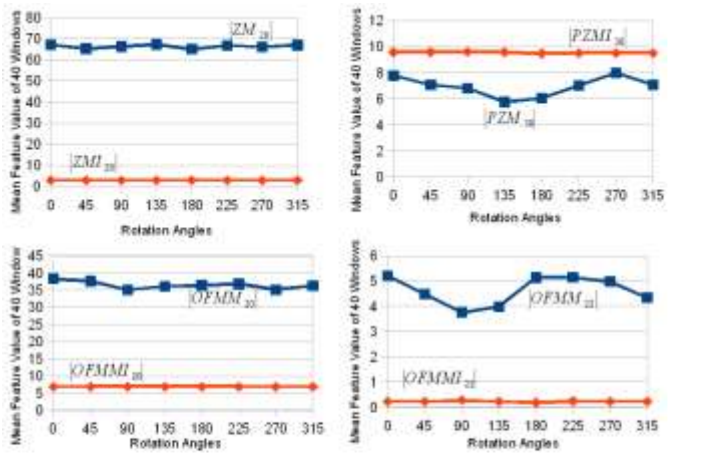
D4

D9

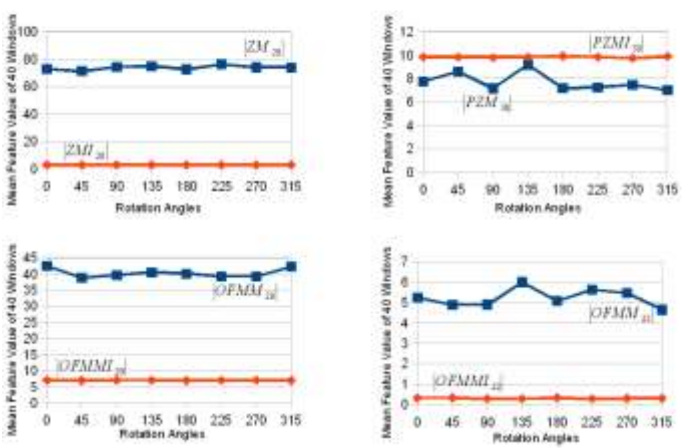


D17

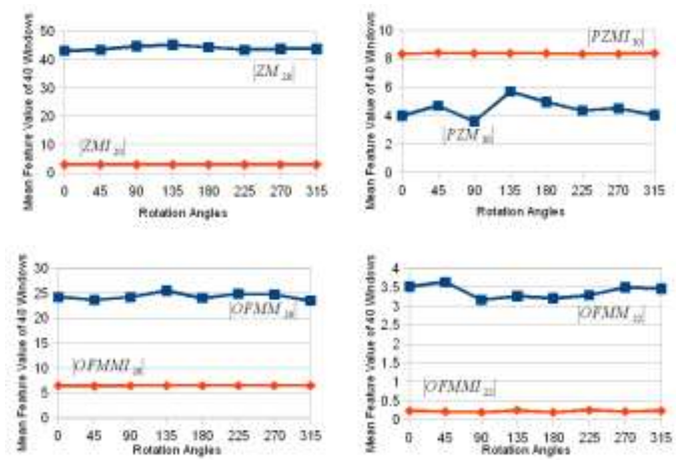
- Texture images rotated by different angles (0, 45, 90, 135, 180, 225, 270, 315 degrees)
- 40 sample windows on each rotated image
- Sample window size is 31
- Compare mean of 40 moment invariants



Rotation invariance evaluation on D4 texture



Rotation invariance evaluation on D9 texture

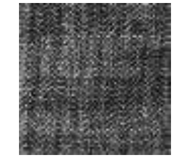


Rotation invariance evaluation on D17 texture

Scaling Invariance: Brodatz Texture

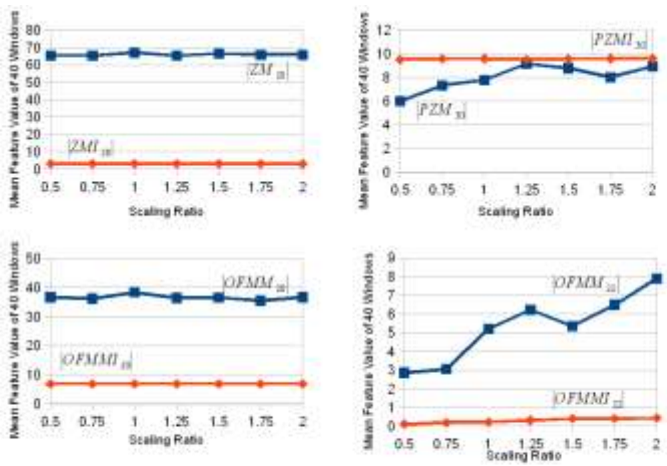
D4

D9

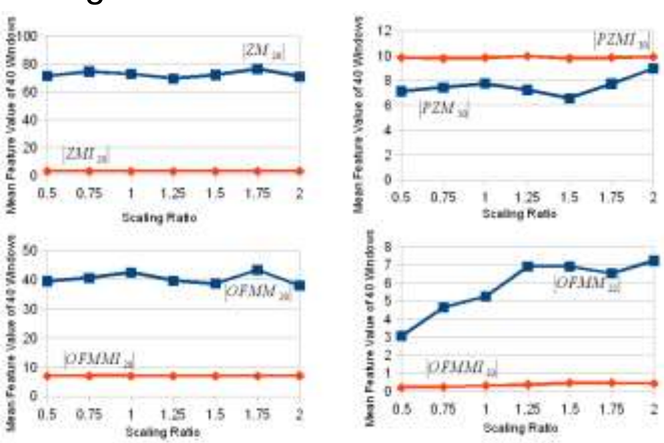


D17

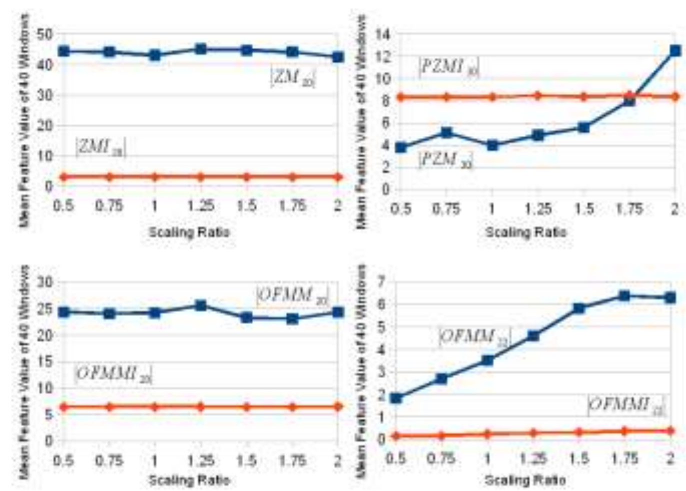
- Texture images scaled by several ratio (0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)
- 40 sample windows on each scaling image
- Sample window size is 31
- Compare mean of 40 moment invariants



Scaling invariance evaluation on D4 texture

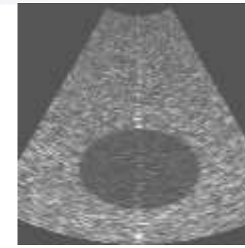


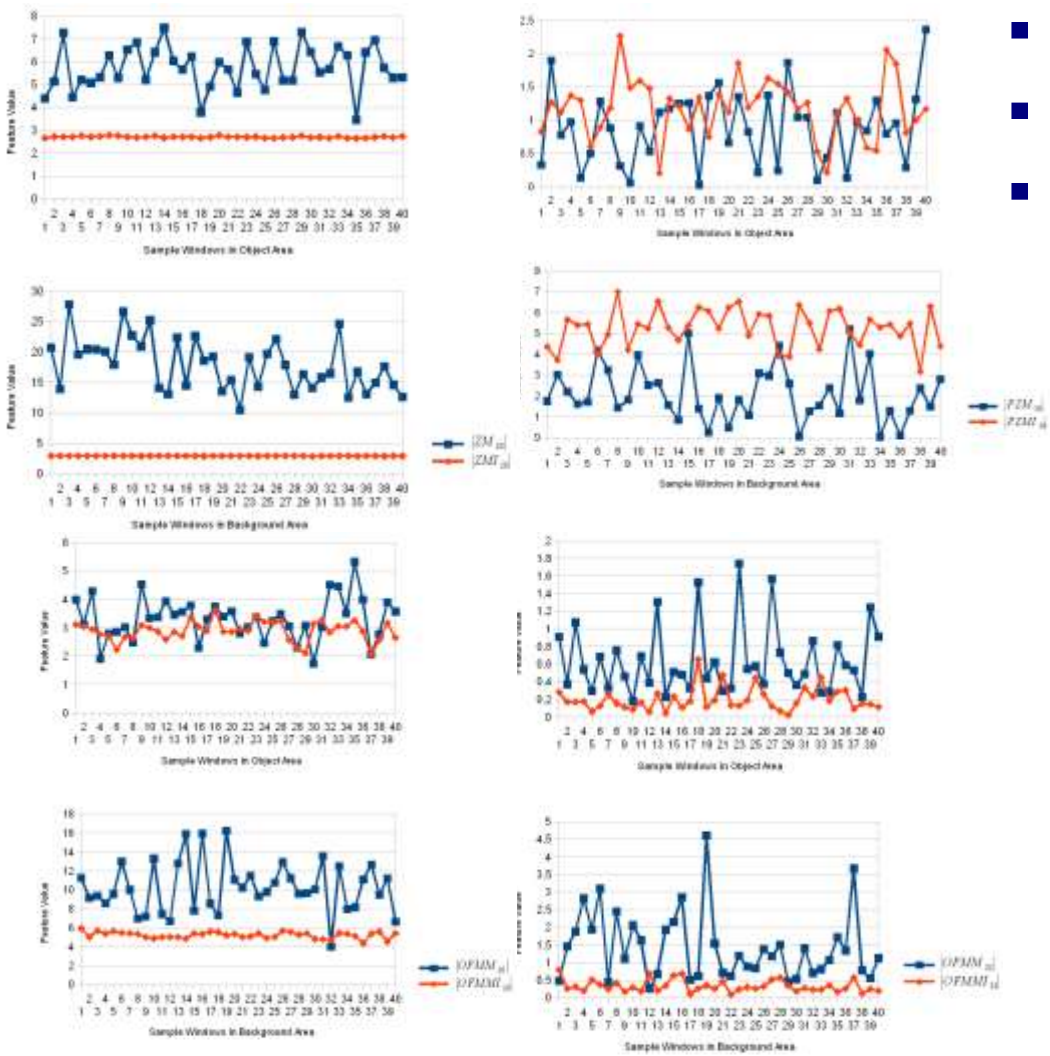
Scaling invariance evaluation on D9 texture



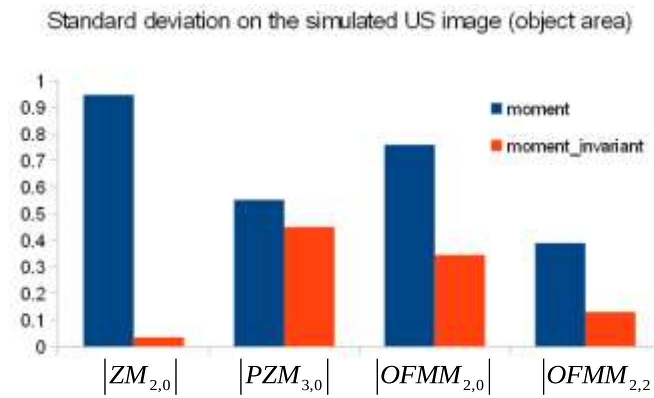
Scaling invariance evaluation on D17 texture

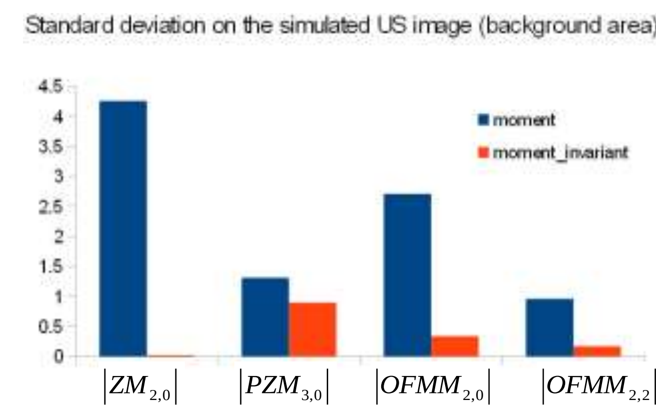
Invariance Evaluation: Simulated Ultrasound Image



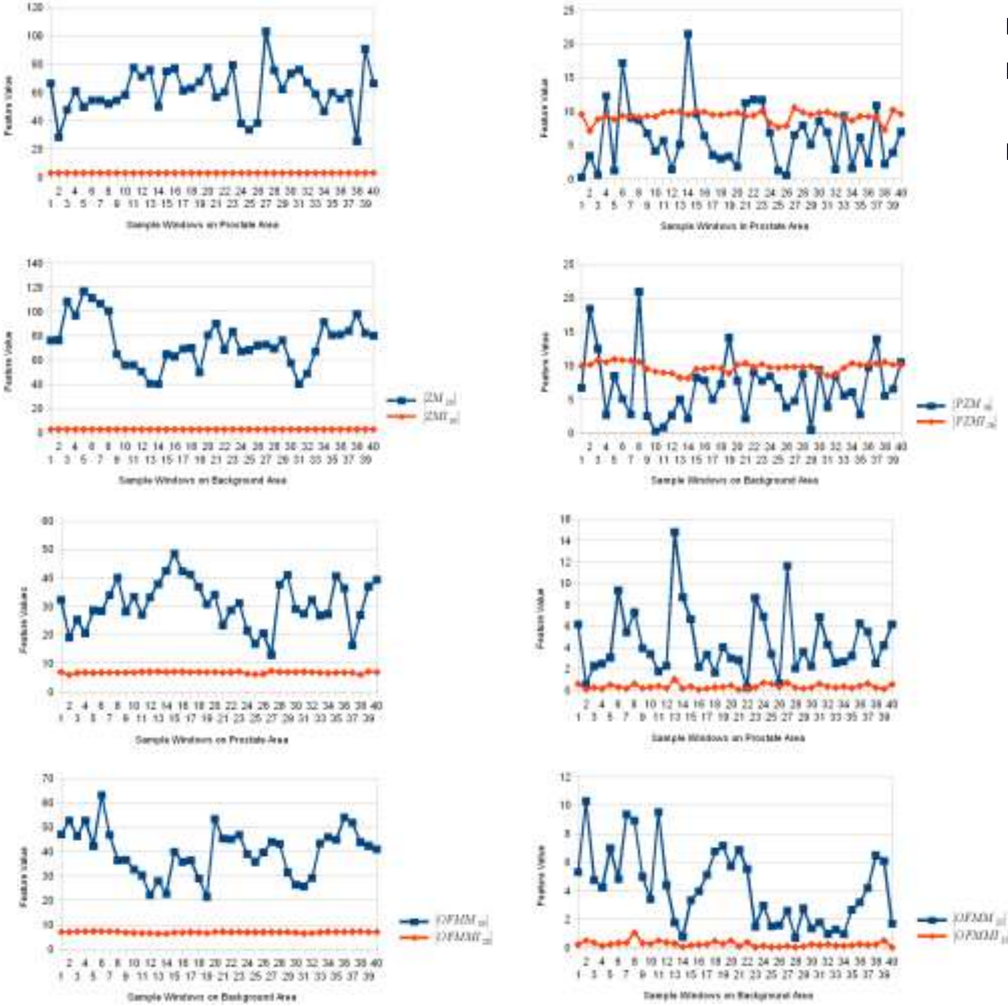


- Simulated ultrasound image with two realistic speckle spatial distribution
- 40 sample windows on object area and background area
- Sample window size is 31

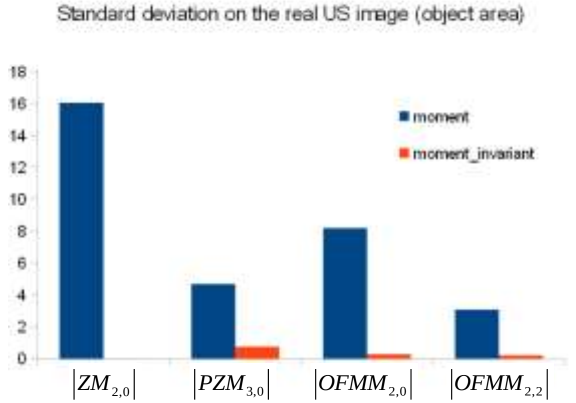


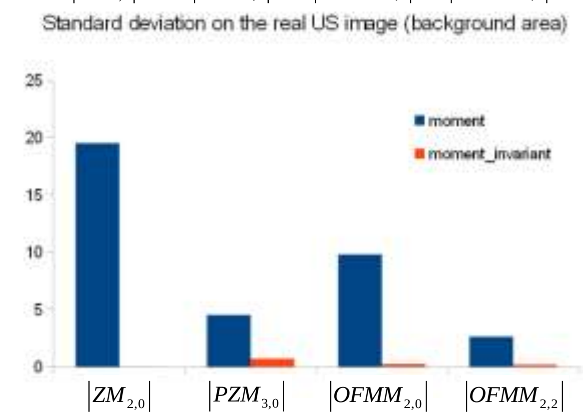


Invariance Evaluation: Real Ultrasound Image



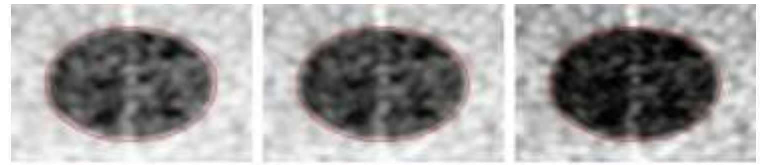
- Real ultrasound image
- 40 sample windows on prostate area and background area
- Sample window size is 31





Order and Repetition Influence

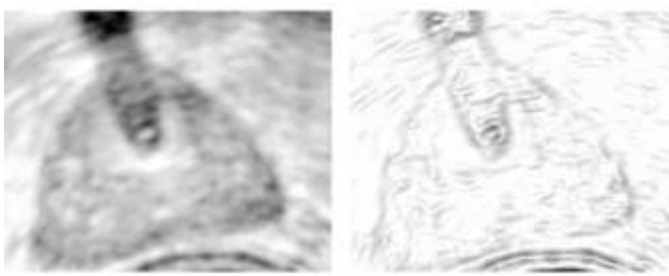
- Order *p*
  - Low influence
- Repetition *q*
  - *q* = 0, regional distribution
  - *q* = 1, “gradient of texture”



$|PZMI_{1,0}|$ $|PZMI_{2,0}|$ $|PZMI_{3,0}|$

$|ZMI_{2,0}|$ $|PZMI_{2,0}|$ $|OFMMI_{1,0}|$

$|ZMI_{3,1}|$ $|PZMI_{2,1}|$ $|OFMMI_{0,1}|$



$|PZMI_{3,0}|$ $|PZMI_{2,1}|$

Summary of Moment Invariants

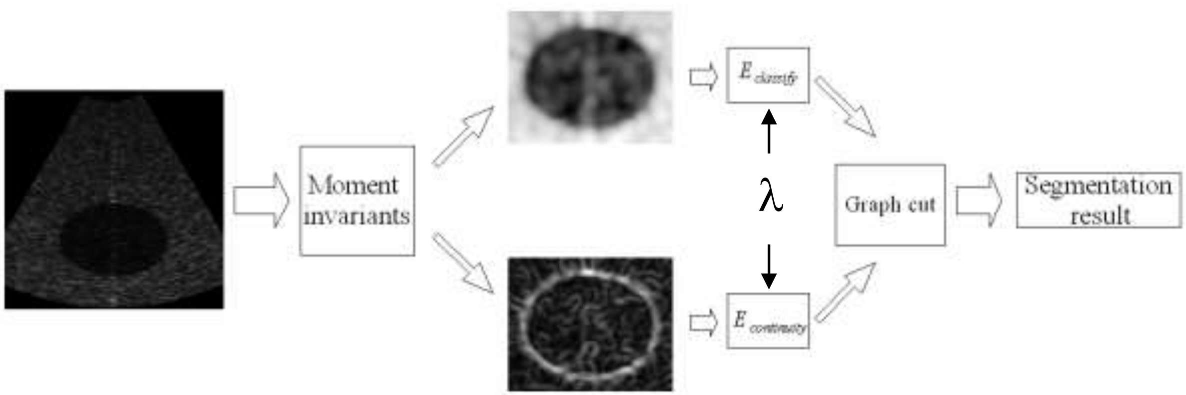
- Invariant to speckle orientation and scaling
- Able to describe texture on simulated and real images
- Able to describe not only regions of similar texture but also the boundaries between two textured regions
  - Could be used in mixed region-boundary based segmentation methods (level sets, active contours, graph cut, etc)

Graph Cut Based Texture Segmentation

- Graph cut algorithm
  - Combined region and boundary based segmentation algorithm
  - Segmentation problematic is formulated by minimize energy function:

$$E_T = E_{classify} + \lambda E_{continuity}$$

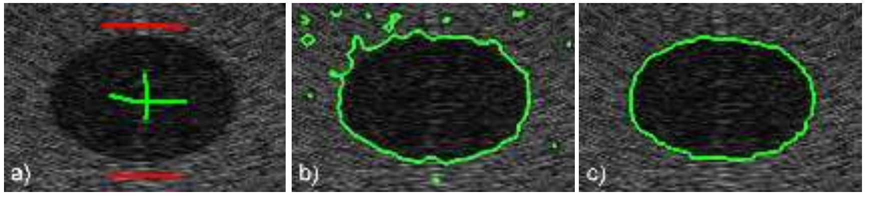
  - $E_{classify}$: Moment invariants with q = 0 give probability that a pixel belongs to the class “object” or “background”
  - $E_{continuity}$: Moment invariants with q = 1 give degree of similarity or discontinuity between two neighboring pixels



Segmentation Framework:

Tuning on Simulated Data

$$E_T = E_{classify} + \lambda E_{continuity}$$



a) Graph cut seed points

b) $\lambda = 0$ with only the regional information

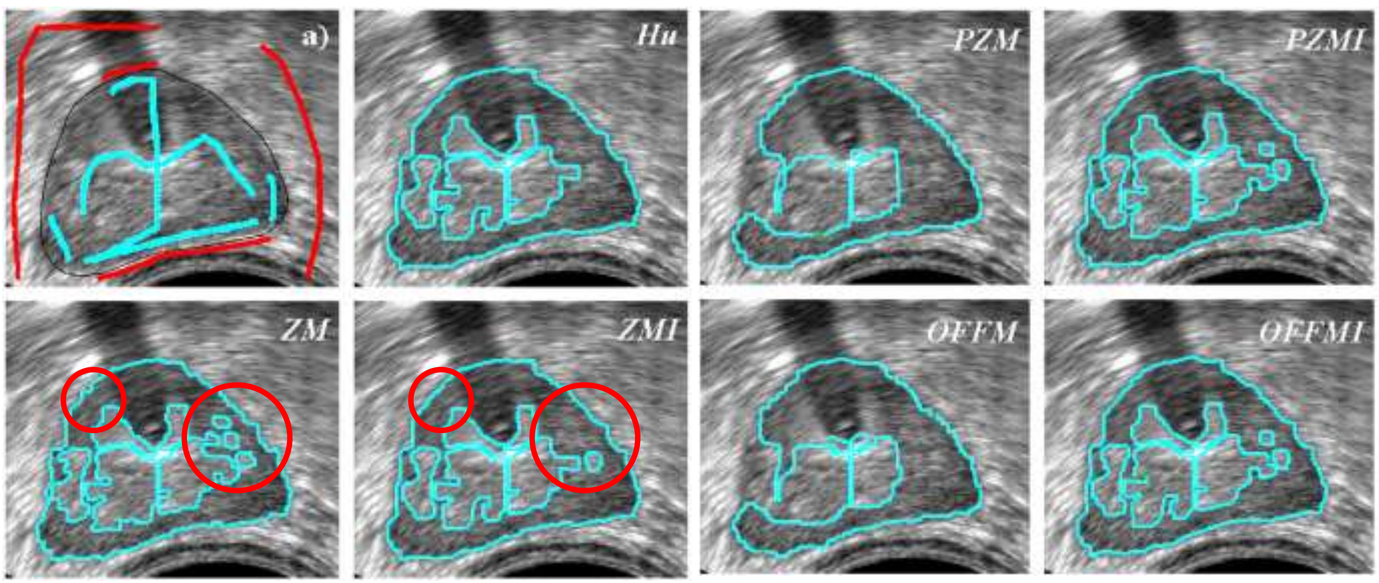
c) $\lambda = 1$ with a mixture of region and boundary information.

- Pixels sampled manually
  - Seed points for segmentation
  - Training basis for weight assignment initialization
- Parameter λ
  - Balance of boundary information
    - Influence is not linear
- Texture features
  - Normal moments
  - Hu's invariants
  - Moment invariants

	Fract area diff	Sensitivity	Accuracy
Hu	-7.8%	91.81%	91.42%
ZM	-4.63%	95.0%	94.63%
ZMI	-6.42%	93.47%	93.36%
PZM	-90.87%	9.13%	9.13%
PZMI	-4.22%	95.33%	94.88%
OFMM	-90.83%	9.17%	9.17%
OFMMI	-2.35%	96.99%	96.33%

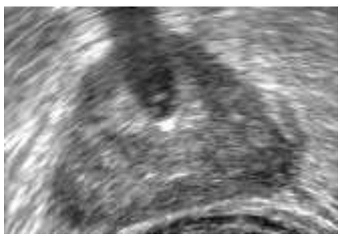
Segmentation: Real Ultrasound Image

- Real ultrasound image
  - Speckle more heterogeneous than that in the simulated ultrasound image
  - Catheter → classical ultrasonic shadow
- Segmentation
  - interactively setting some well adapted seed points
  - Change window size to 11×11 to adjust it to the transrectal prostate speckle dimension
  - λ is set to 1

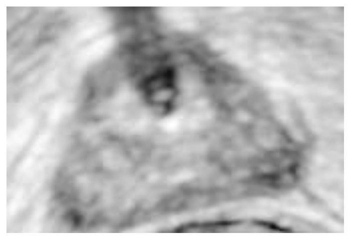


Intensity-based Registration

- TRUS image



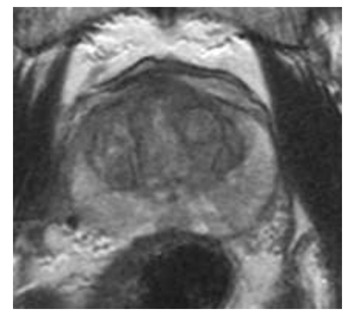
Speckle distribution



Intensity distribution

- Homogeneous information using moment invariants with repetition $q = 0$

- T2 MR image



Axial view

Sagittal view

- The prostate is heterogeneous in values
- Some prostatic zone share common intensity distribution with neighbor tissues

Difficulty to make intensity-based registration

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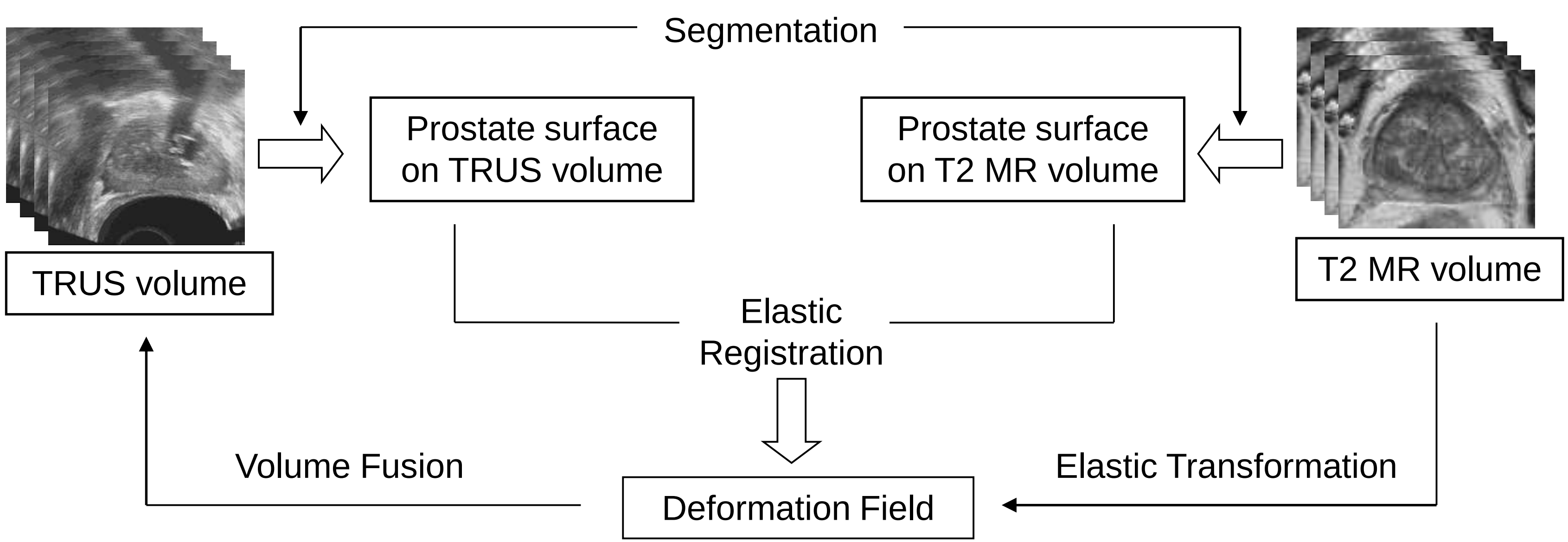
Feature-based Registration

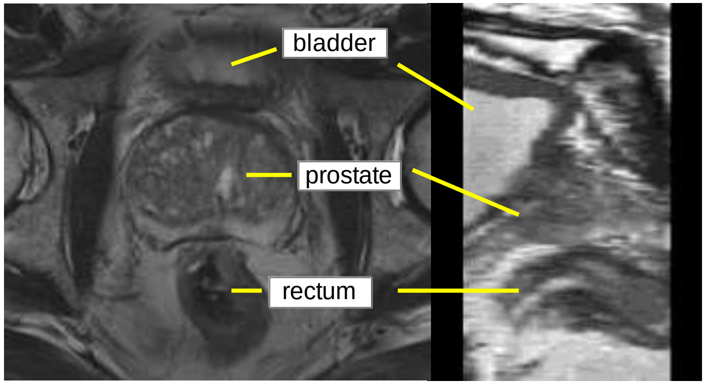
- Common feature is necessary on both imageries
  - Geometrical features (points, lines or surfaces) extracted from anatomical or external implanted structures
- Problem
  - TRUS and T2 MRI share little common information
    - TRUS images: low structure information, except external surface and partially the urethra
    - T2 MRI: rich internal features (prostate zones, tumors) but external surface not real clear
- Solution
  - Prostate surface segmentation
  - Surface-to-surface registration



Prostate Surface Segmentation

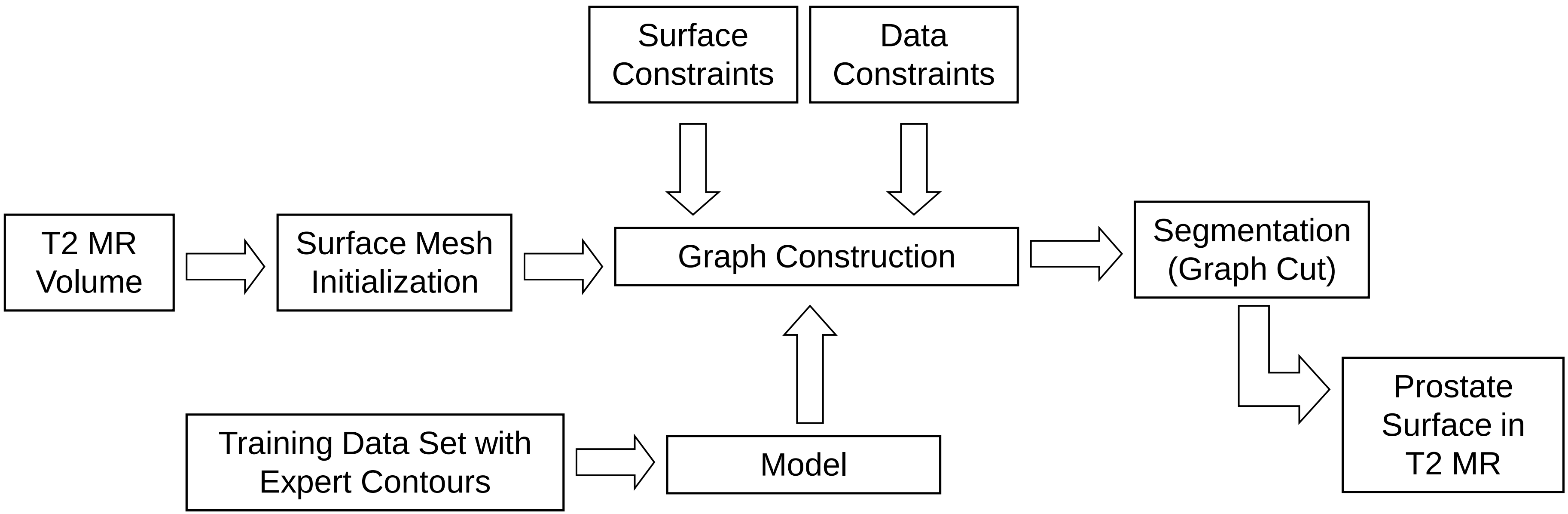
- TRUS 3D segmentation
  - The work in (Garnier et al. 2011)
    - Discrete dynamic contours (DDC)
    - Optimal surface detection (OSD) (Li et al. 2004)

- T2 MRI 3D segmentation
  - T2 MRI
    - Inhomogeneous intensity distribution inside prostate
    - Surface information is closed to neighbor organs (bladder, rectum)
    - Low resolution in the third direction, especially apex and base
  - Solutions
    - OSD segmentation
      - Model based methods
      - Multiple objects framework



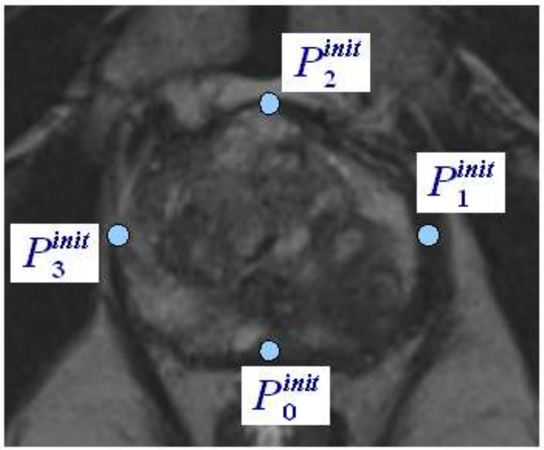
Li, K., et al. (2004).Efficient optimal surface detection: theory, implementation, and experimental validation. Medical Imaging 2004, International Society for Optics and Photonics.

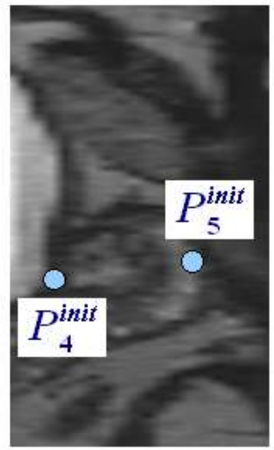
OSD based Segmentation Scheme

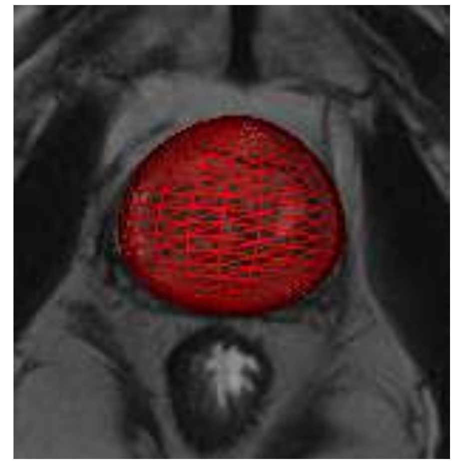


- Surface mesh initialization
- Graph construction
- Graph cut segmentation

Initialization

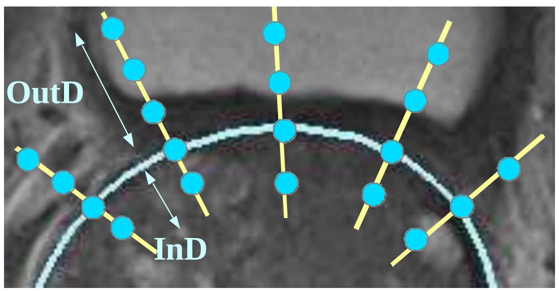


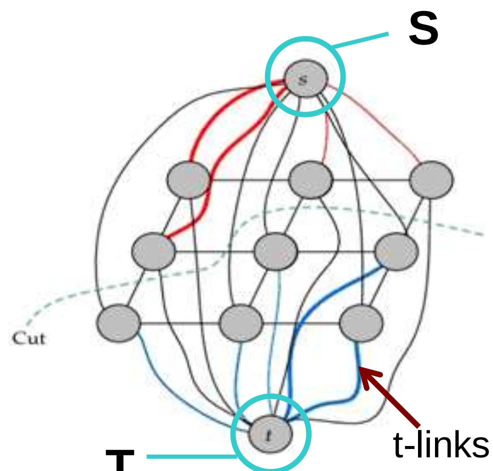


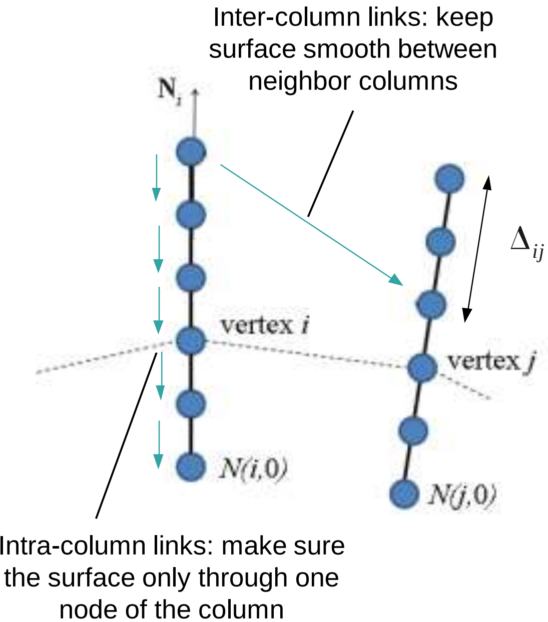


- Manual initialization to include user expertise
  - Six initial points: four in a central axial plane, one on the apex and one on the base
  - 3D ellipsoid adjusted to the initial points using a Biharmonic Spline surface → initial mesh

Graph Construction

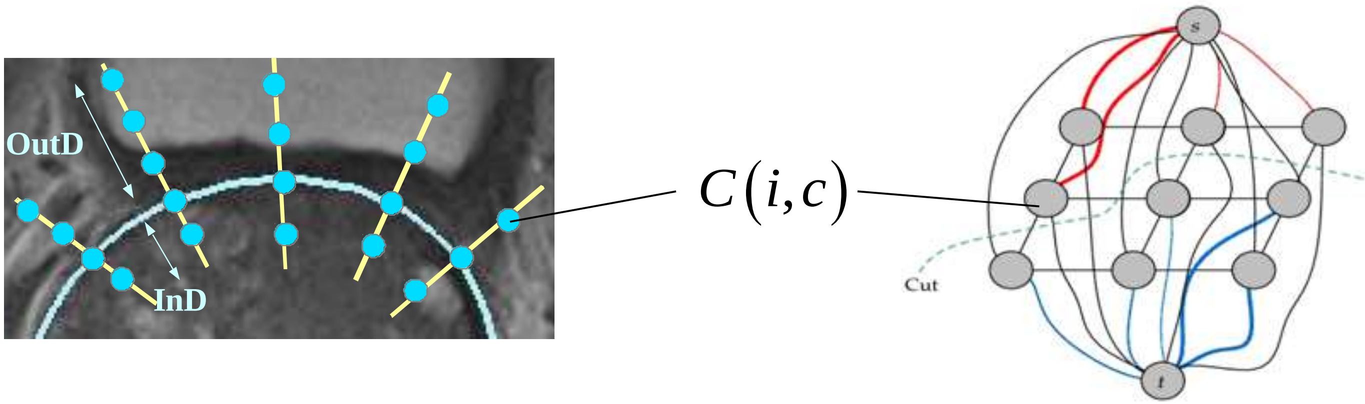






- Nodes
  - Object nodes
    - Vertex of initial mesh
    - Nodes distribute inside and outside of surface along the normal cross vertexes
  - Terminal nodes
- Links
  - n-links: links between object nodes (**surface constraints**)
  - t-links: links between object nodes and terminal nodes (**data constraints**)

Data constraints



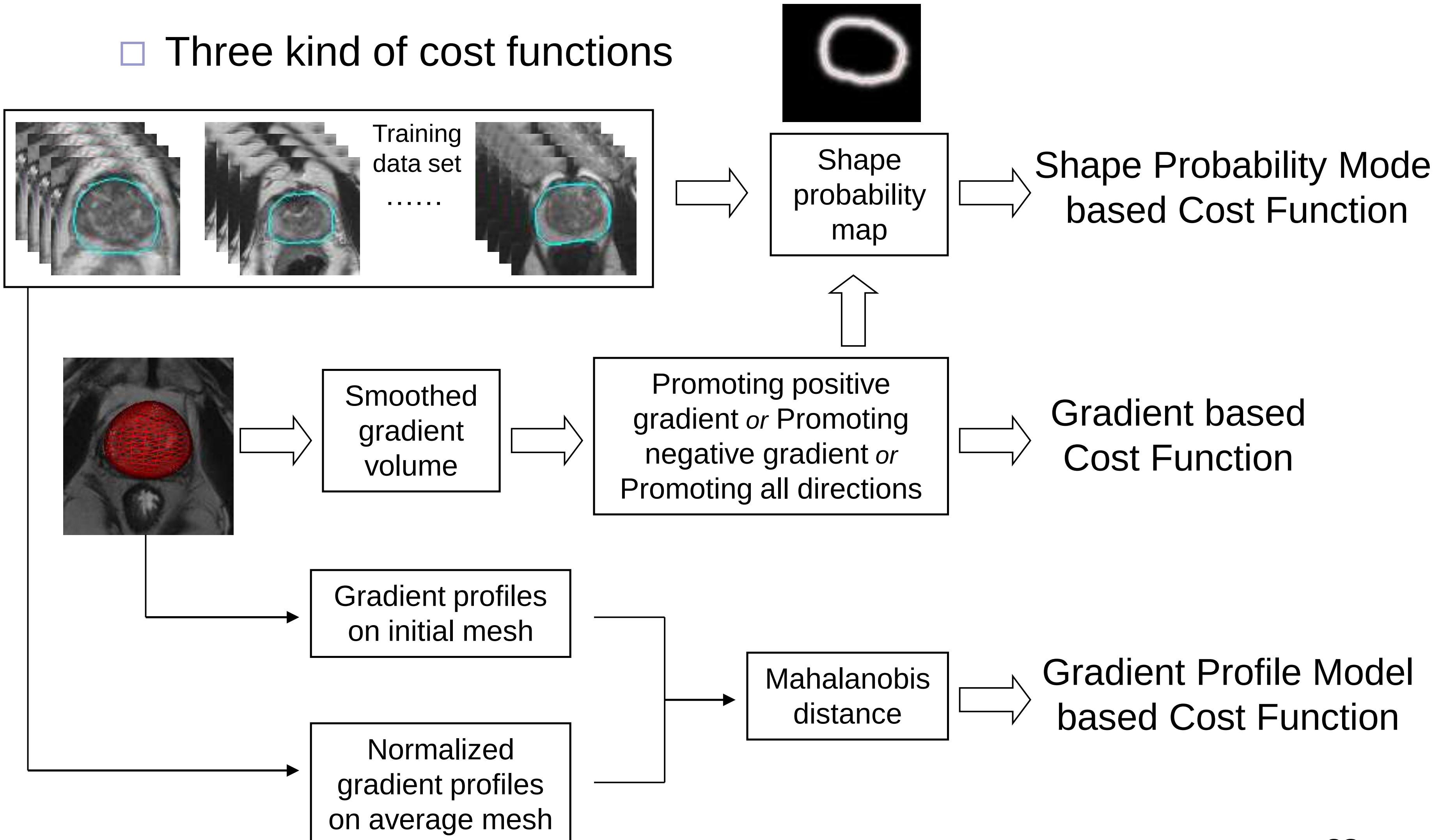
- For each node, cost function ***C*** is related to the possibility that the node belongs to the target surface.
- Weight $w(i,c)$ is assigned to each node cost $C(i,c)$:

$$w(i,c)=\begin{cases} C(i,c) & \text{if } c=0 \\ C(i,c)-C(i,c-1) & \text{otherwise} \end{cases}$$

- 6 initial points assigned to a very high negative cost

Cost Functions

- Three kind of cost functions



Material and Parameters

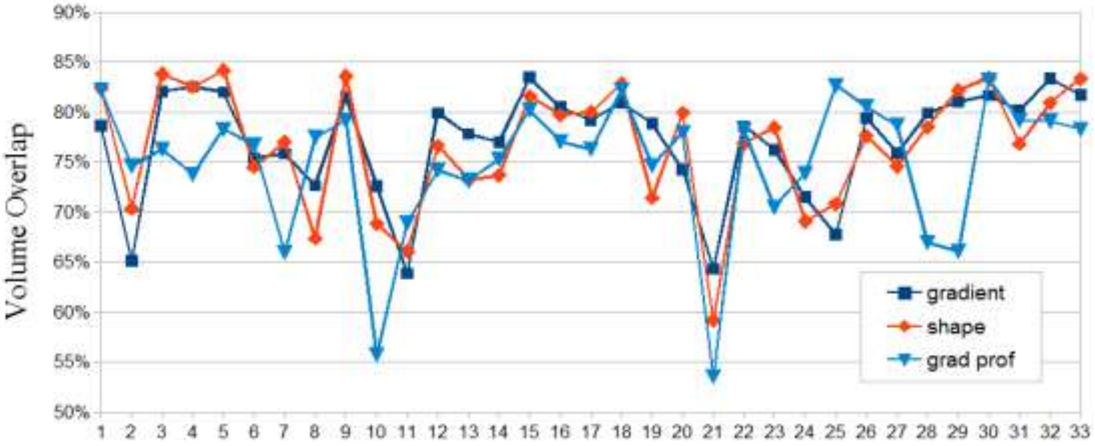
- 33 T2 MRI data with ground truth designed by expert

MRI system	Number	Size (voxel)	s_t (mm)	s_a (mm)
3T Philips Achieva	10	$720\times720\times20$	0.416	4.001
3T Siemsens Vero	5	$320\times320\times20$	0.625	3.600
1.5T Siemens Magnetom Symphony	16	$256\times256\times24$	0.781	3.000
3T Philips Achieva	1	$352\times352\times24$	0.540	2.630
GE Signa HDxt	1	$512\times512\times16$	0.391	4.500

  - In model based cost function calculation, 1 case is chosen as to be segmented volume, and the other 32 cases with expert contours are used as training data set to create models

- Parameter tuning
  - OSD method depends on 5 parameters (eg. search distance, promoted gradient direction, etc)
  - Parameter tuned separately on all 33 datasets, and keep the parameter values which give the best global performance compared to expert segmentations

Result of Single OSD



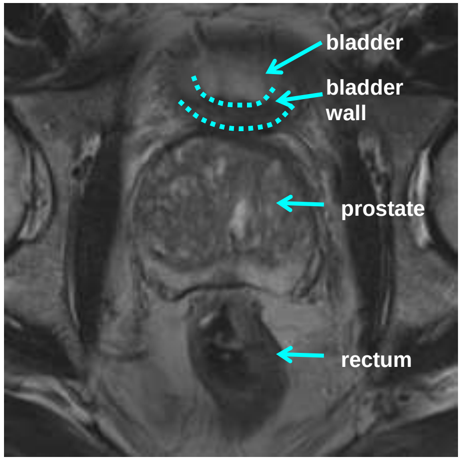
$$VO = \frac{V_{ref} \cap V_{seg}}{V_{ref} \cup V_{seg}}$$

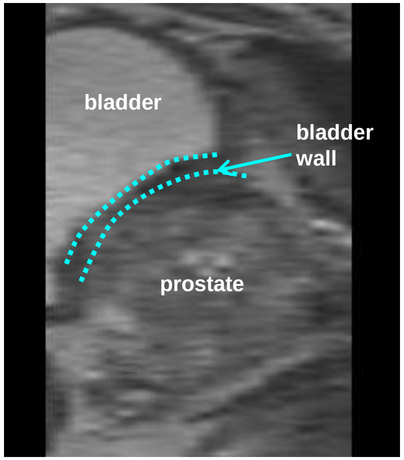
Volume overlap (VO) metric for all the 33 volumes with different cost function models

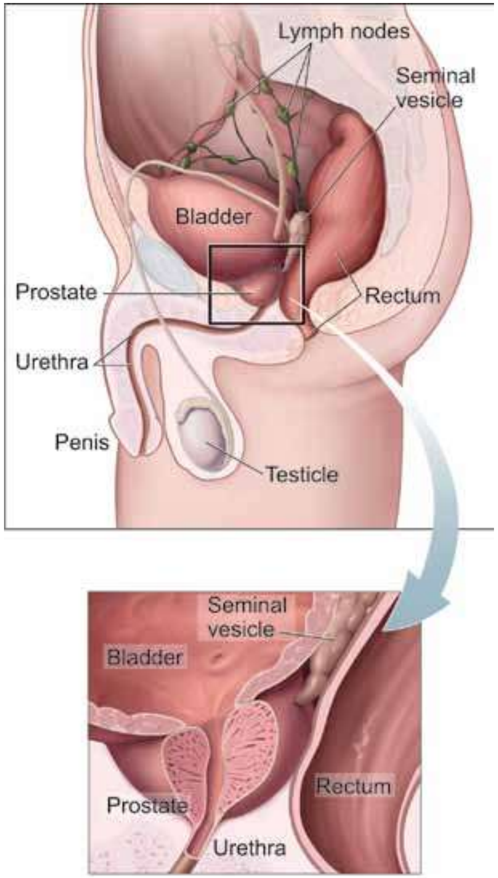
- Shape probability and gradient profile model
  - In some cases they can increase the performance.
  - They also can lead to very poor results
    - Prostate shape variability
    - Heterogeneity and bad resolution in third direction
- Best global results: the gradient based cost function with all directions give a mean volume overlap of 72% with a standard deviation of 5.5%

Limitation of Prostate OSD

- Surrounding organs
  - Bladder wall
    - Similar intensity to prostate surface
    - Thickness variant in 2D view
  - Rectum
    - Globally curved form
    - Highly heterogeneous
- Solution
  - Competition between organ information
  - Multiple objects OSD (Song et al. 2010)



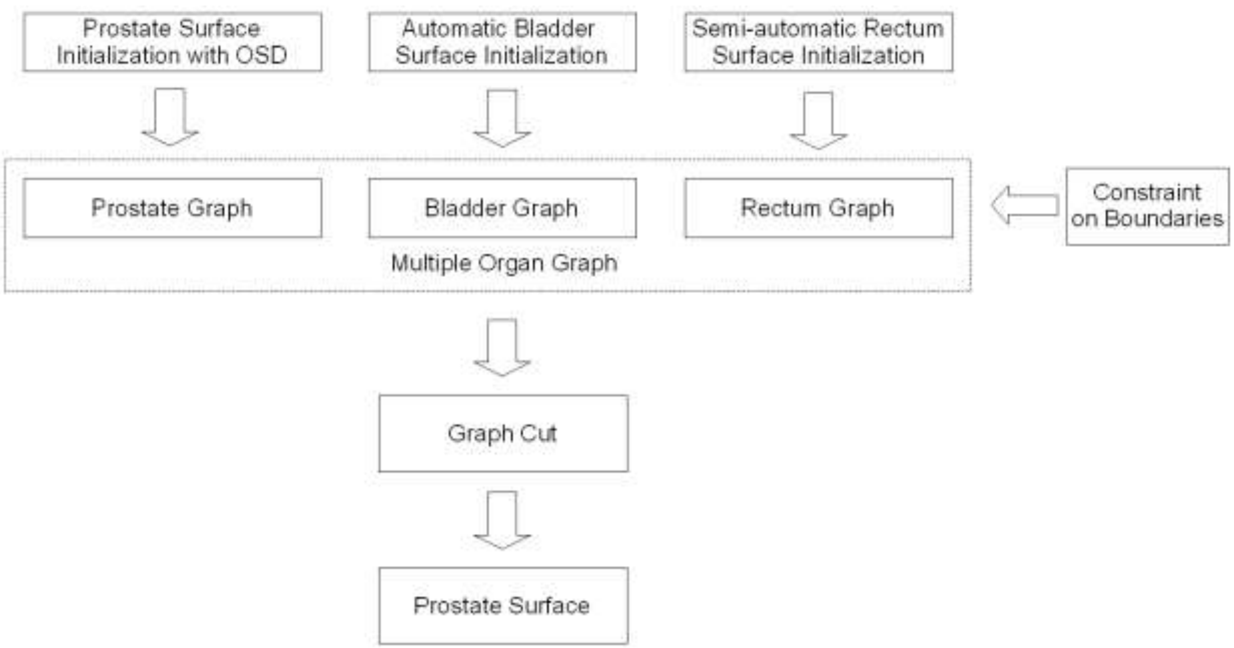




Song, Q., et al. (2010). Graph search with appearance and shape information for 3-D prostate and bladder segmentation. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2010, Springer: 172-180.

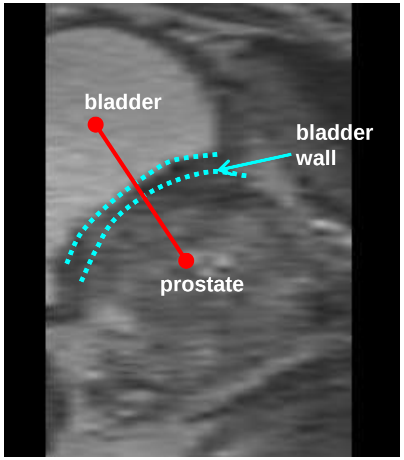
Workflow of Multiple Objects OSD

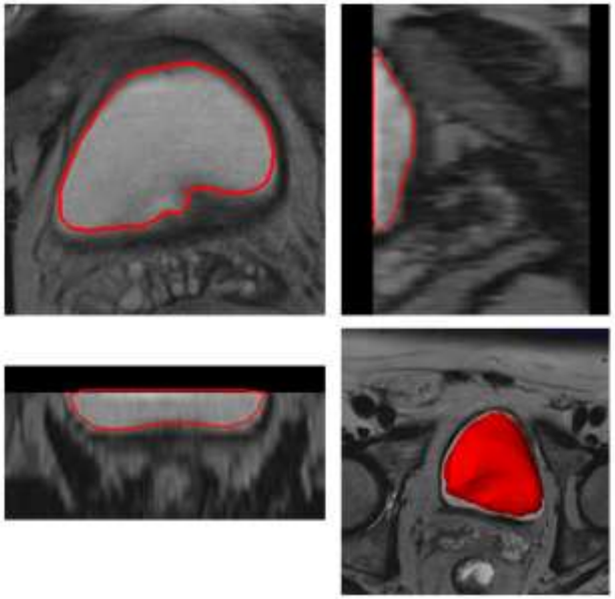
- Initial surface meshes are built for all three organs
- Graphs are built for all the organs. These graphs will share some common nodes at the same location. Some anatomical and competition constraints will be set at these nodes.
- Graph cut will be used to estimate the surfaces of all the graphs
- We keep the prostate surface as segmentation result.



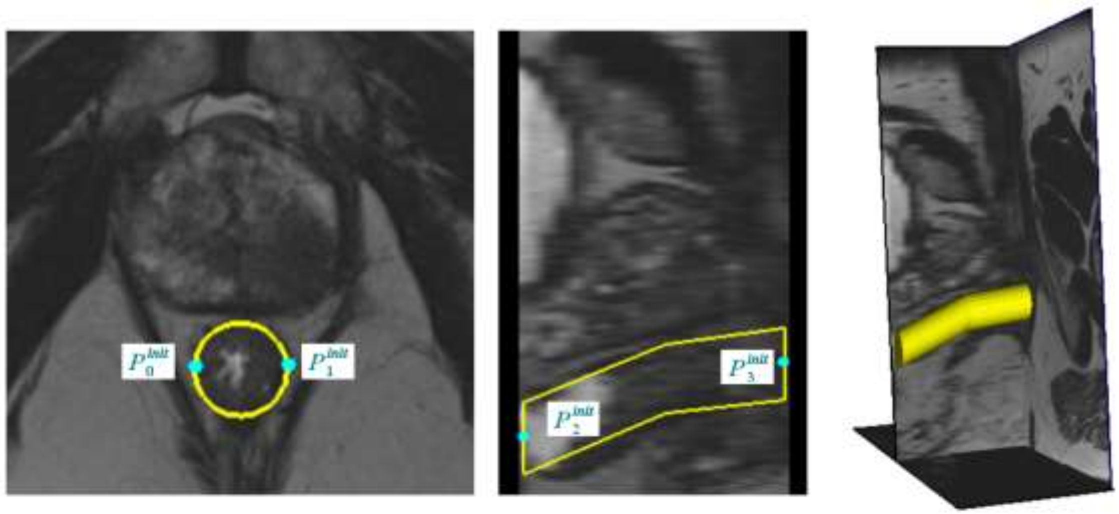
Initialization of Bladder

- Automatic bladder segmentation
  - In T2 MRI, urine seen as hyper-signal
  - Bladder superior position to prostate
    - Automatic 3D seed point for discrete dynamic contour (DDC)
    - Inner wall segmentation



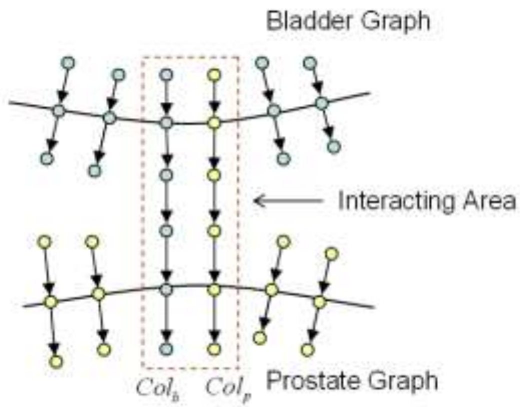


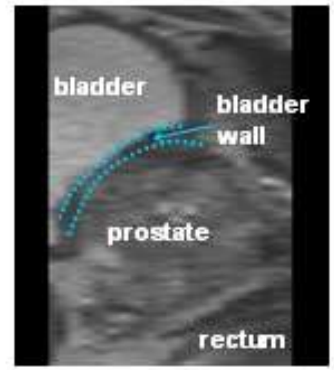
Initialization of Rectum



- Fast 3D broken tubular model
- Four initial points
  - Two on the middle slice to define lateral diameter
  - One in front of prostate in the middle of rectum, One behind the prostate in the middle of rectum, give the axes directions of the broken tube

Multiple Objects Graph Construction





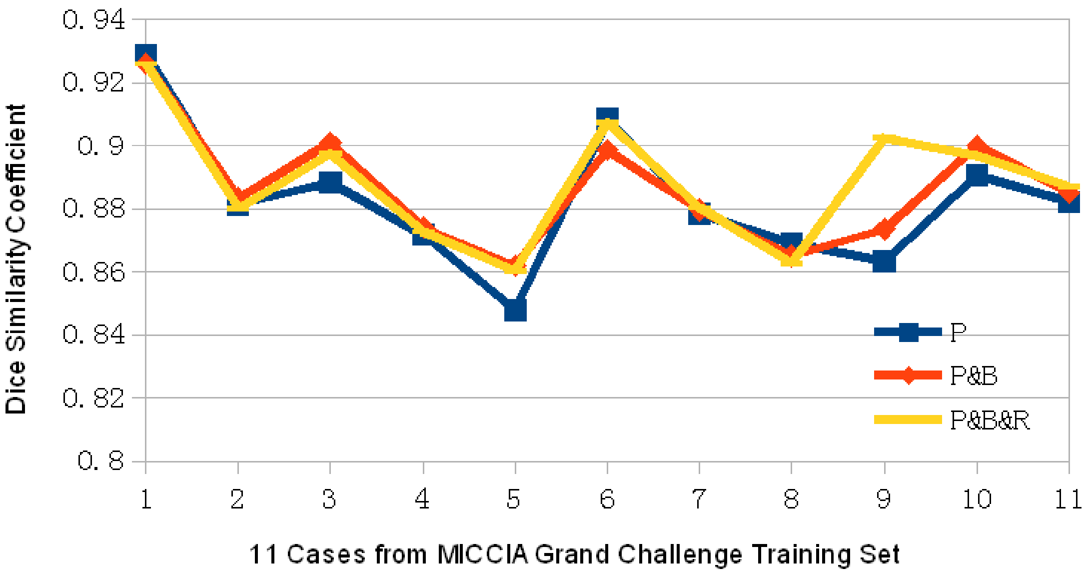
- Interacting area definition and surrounding organ surface adjustment
- Node columns belong to different graphs in interacting area share the same position
- Interacting links make sure surfaces keep distance to each other
- The bladder wall thickness (3-5 mm) information is assigned to graph weights

Evaluation of Multiple Objects OSD

- 33 T2 MR volumes with expert contours as training data for tuning parameters
- Evaluate on 11 T2 MR volumes from the MICCAI Grand Challenge: PROMISE 2012 training dataset
- Calculate dice similarity coefficient (DSC) between segmented data and the manual delineated volume provided by the challenge

$$DSC = 2 \cdot \frac{V_{ref} \cap V_{seg}}{V_{ref} + V_{seg}}$$

Results of Multiple Objects OSD



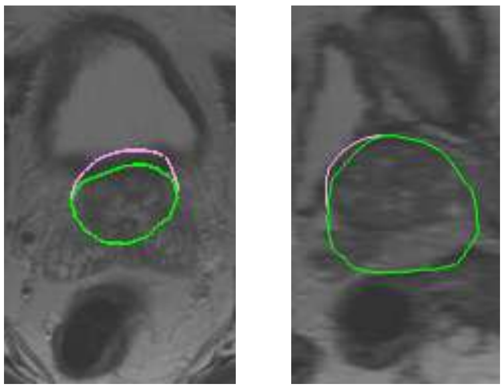
P means single **P**rostate OSD segmentation;

P&B means **P**rostate-**B**ladder multiple objects OSD segmentation;

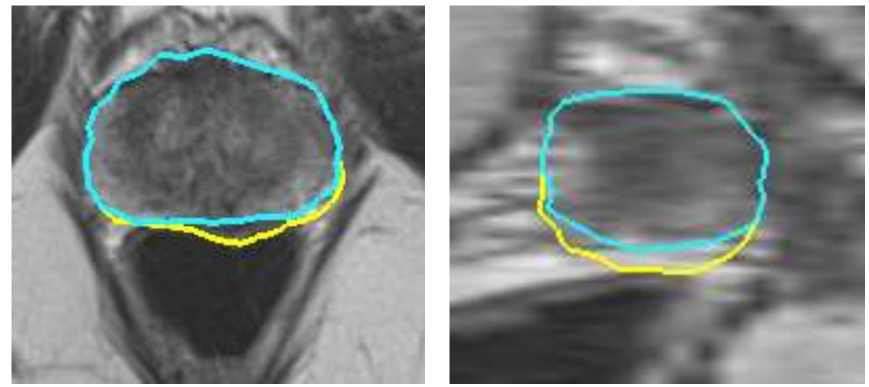
P&B&R means **P**rostate-**B**ladder-**R**ectum multiple objects OSD segmentation

	Mean DSC	Median DSC
Single prostate OSD	0.8828 (0.02)	0.8814
Multiple object OSD (P&B)	0.8862 (0.02)	0.8833
Multiple object OSD (P&B&R)	0.8884 (0.02)	0.8870
Vincent, et al (best competitor of MICCAI Grand Challenge)	0.88 (0.03)	0.89

Results of Multiple Objects OSD

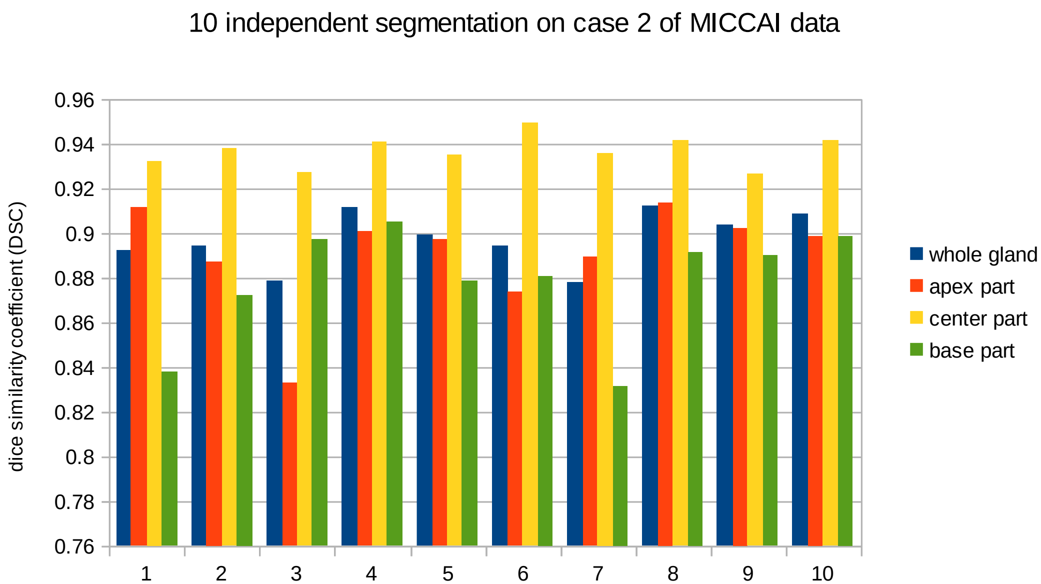


The result of single OSD (pink) and Prostate-Bladder OSD (green) on Axial and Sagittal plane of Case 3



The result of Prostate-Bladder OSD (yellow) and Prostate-Bladder-Rectum OSD (cyan) on Axial and Sagittal plane of Case 11

Intra-observer Variance of Initial Points



DSC	Whole gland	Apex zone	Center zone	Base zone
mean	0.8971	0.8906	0.9366	0.8782
std	0.0123	0.0234	0.007	0.0252

- 10 independent segmentations of one case with multiple objects (prostate-bladder-rectum) OSD
- On each segmentation: define interactively 10 initial points

- Center zone: highest and most stable DSC scores
- Apex and base zones: higher initial points definition influence

Conclusion:
T2 MRI Segmentation

- OSD based segmentation
  - Estimate prostate surface with minimal interactivity
  - Include user expertise
  - Multiple-objects framework prevent prostate surface leak to surrounding organs
- Discussion
  - The segmentation accuracy of center zone are higher and more stable
  - The segmentation of apex and base zone have relatively good results, but show more inter-observer variance

Outlines

- Background of research
  - Prostate cancer and treatment
  - Ablatherm HIFU device and MULTIP Project
- Region Based Information Characterization in Ultrasound Image
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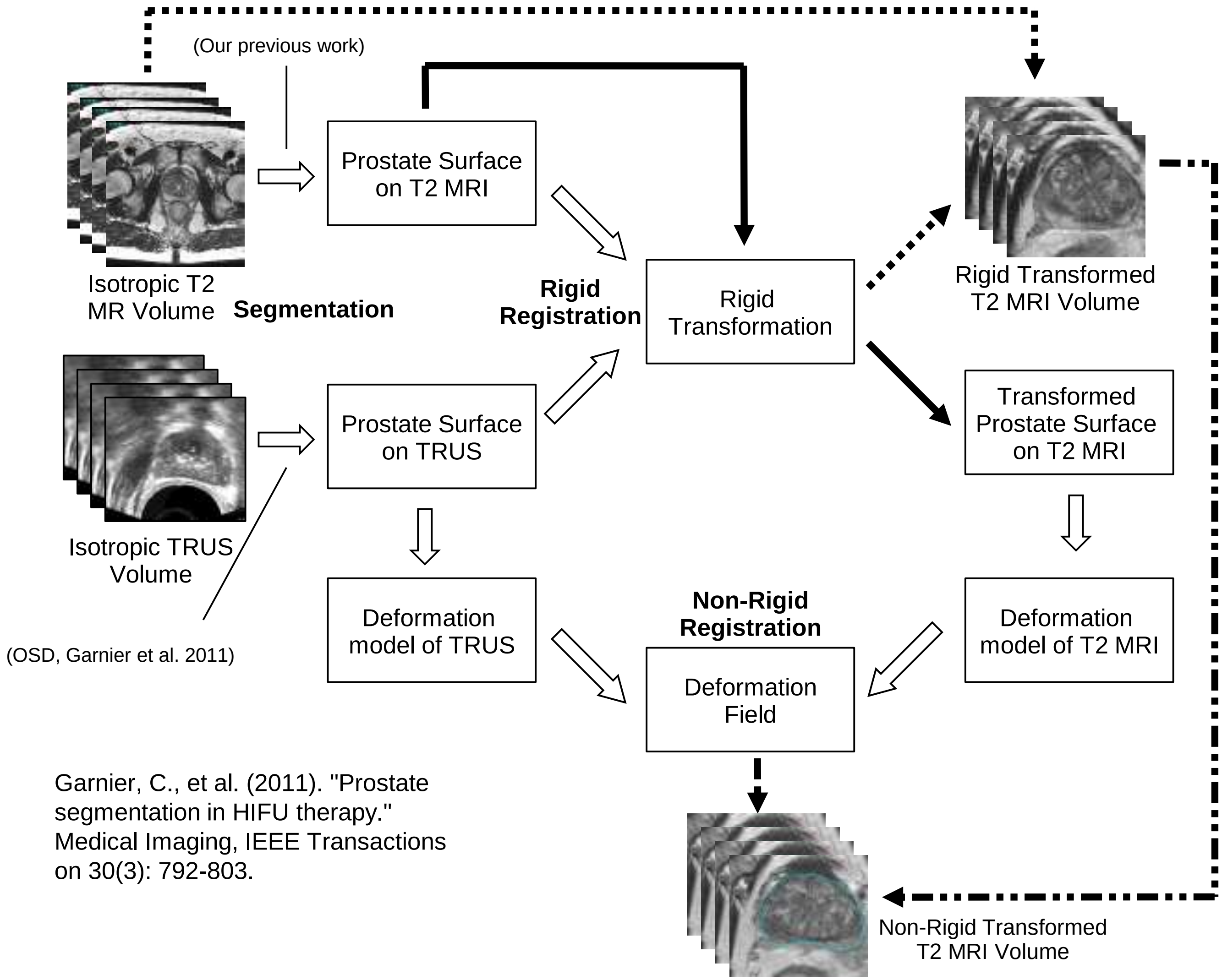
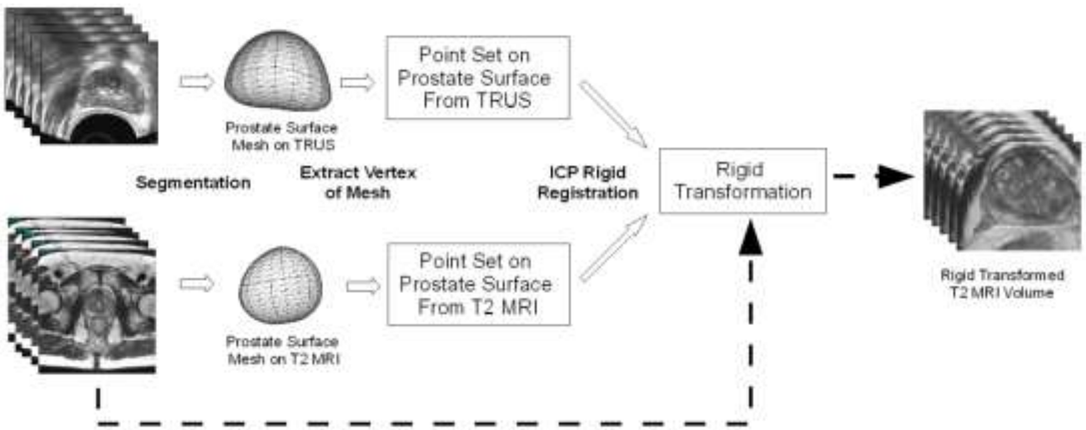
Registration and Fusion Scheme



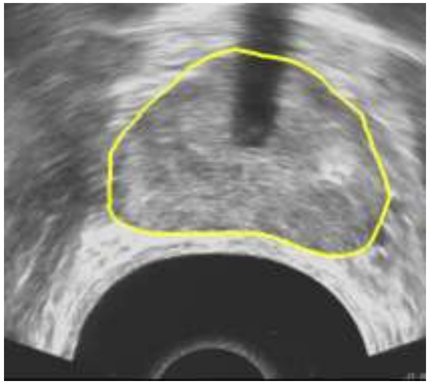
- Rigid registration
  - Align prostate volume and surface
  - Generate initial transformation for next step
- Elastic registration
  - Generate deformation field adjust prostate surface from T2 MR volume to TRUS volume
  - Apply deformation to T2 MR volume to fusion information

Garnier, C., et al. (2011). "Prostate segmentation in HIFU therapy." Medical Imaging, IEEE Transactions on 30(3): 792-803.

Rigid Transformation

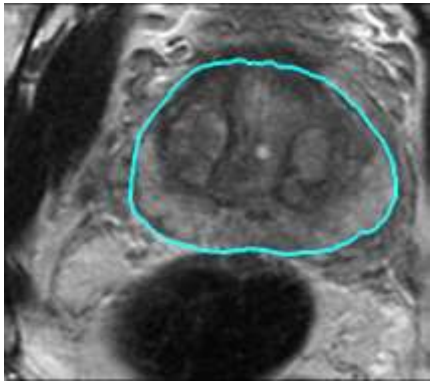


- The vertex of surface meshes are set as surface points
- Iterative Closest Point (ICP) algorithm used to generate rigid transformation between surface point sets
- Apply transformation to T2 MR volume to align prostate between different imaging modalities volumes



TRUS image with contour

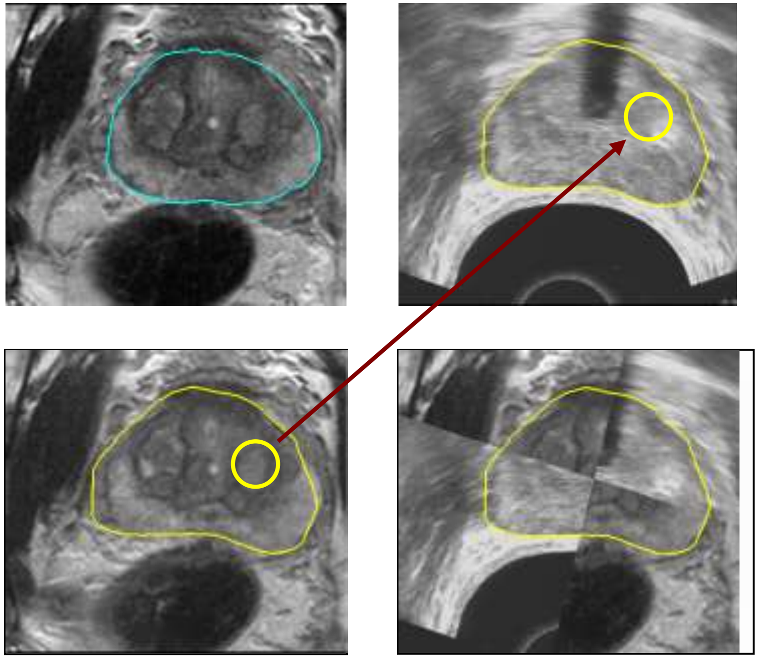
T2 MRI with contour



T2 MRI with contour after rigid registration

Elastic Registration

- Purpose
  - Not simply fitting surfaces
  - Find a 3D deformation field to deform both surface and inside of prostate
  - Map information from T2 MRI to TRUS
- Elastic registration
  - The demons algorithm (Thirion. 1998) in multi-resolution registration framework
    - Only surface information
    - Normalized distance map (Dréan et al. 2012)



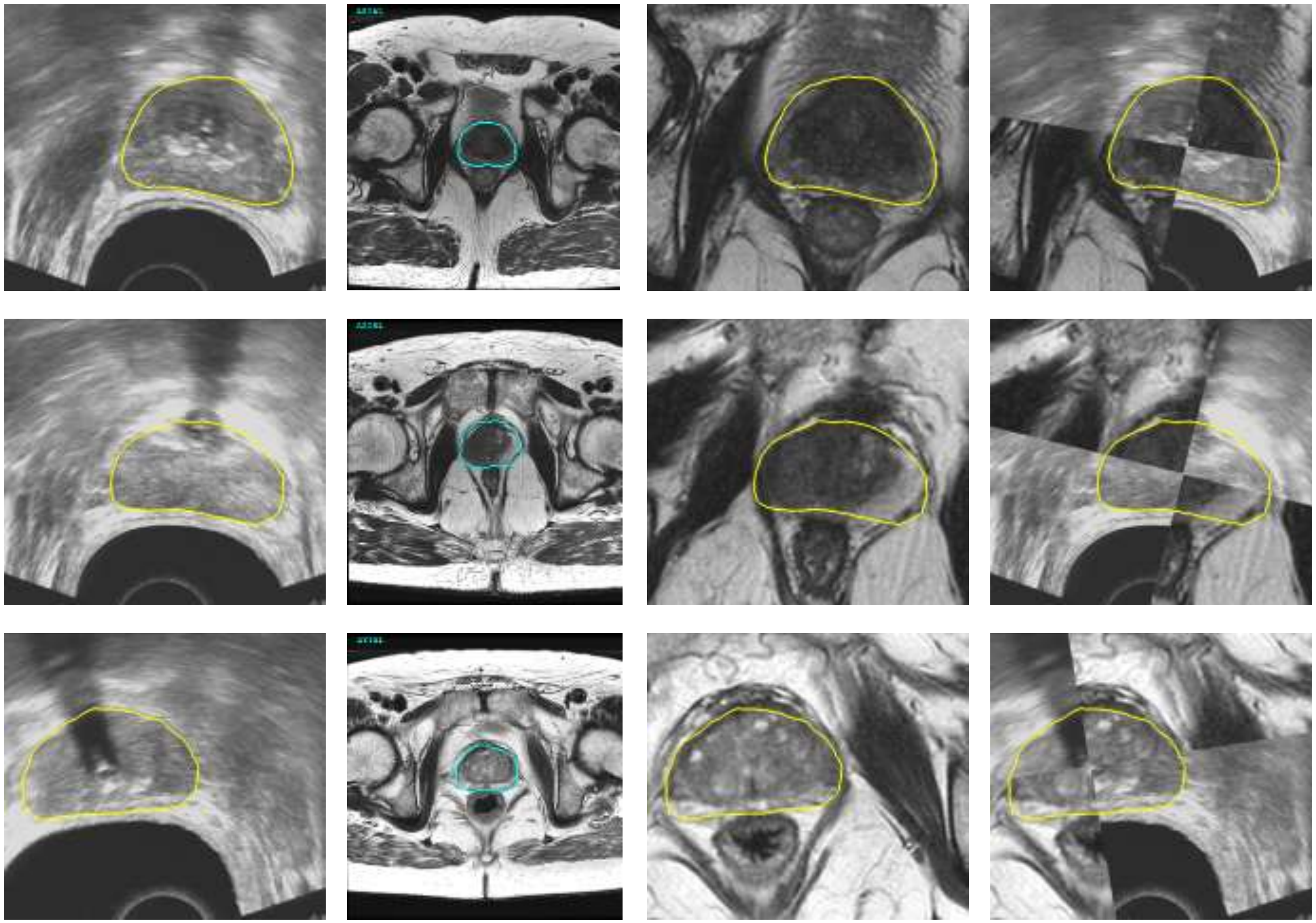
Thirion, J.-P. (1998). "Image matching as a diffusion process: an analogy with Maxwell's demons." Medical Image Analysis 2(3): 243-260.

Dréan, G., et al. (2012). Inter-individual organ-driven CT registration for dose mapping in prostate cancer radiotherapy. Biomedical Imaging (ISBI), 2012 9th IEEE International Symposium on, IEEE.

Feasibility Study - Materials

- 10 clinical cases pre-operative T2 MRI volumes and the intraoperative TRUS volumes recorded on the Ablatherm device (provided by edap-tms)
- No ground truth and inside landmarks on both imaging modalities

Registration Results

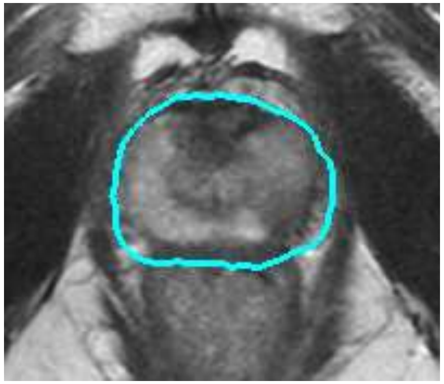


TRUS with contour | T2 MRI with contour | T2 MRI after registration | TRUS/T2 MR fusion

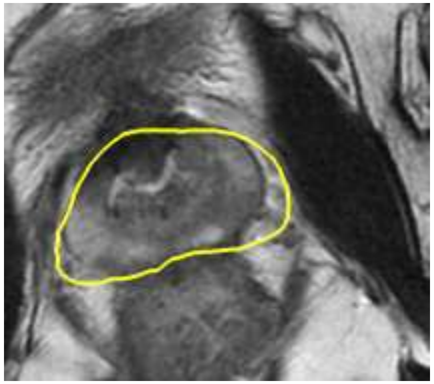
Influence: Surface Segmentation

- Segmentation accuracy
  - The volume overlap (VO) between segmented surface and ground truth on TRUS volume is about 81~87%
  - The volume overlap (VO) between segmented surface and ground truth on T2 MRI is about 80%
  - Segmentation results on both modalities have good accuracy in the medial prostate zone but a lower accuracy at the apex and base zone
- Registration accuracy
  - Highly depending on the surface segmentation accuracy

TRUS volume with segmented contours

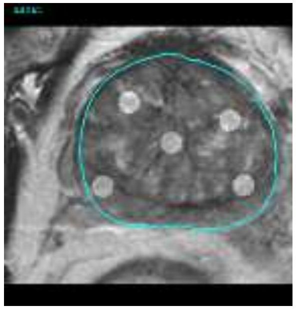


T2 MR volume with bad contours

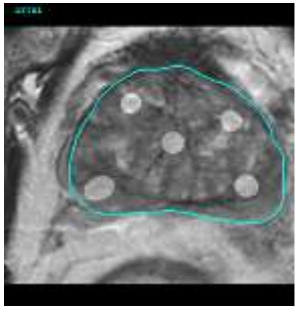


Low accuracy registration

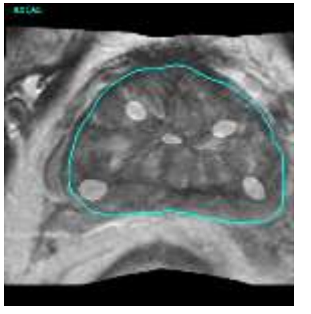
Influence:
Deformation Field Model



T2 MR before
elastic registration



Elastic registration
with binary model



Elastic registration with
normalized distance map model

- **Binary model** deforms areas around boundary, but have little influence in areas away from boundary
- **Normalized distance map model** have influence on all the inner prostate structures, but the deformation of the structures can have an unnatural aspect

- Demons registration gives a good deformation around the surface, but have little warranty to the inside of the prostate

Conclusions:
Surface based registration

- A first attempt to realize the whole registration framework.
- Elastic registration method is able to give a first estimate of the lesion location in the TRUS image.
- Lack of contour ground truth and volume ground truth. The accuracy of the registration still need to be validated.
- Other deformation models should be investigated and evaluated according to some ground truth to increase the accuracy of registration inside the prostate.
- Statistics of the real prostate deformation

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Conclusion:
The Thesis

- Purpose
  - Fusion T2 MRI information and TRUS information to guide HIFU focal therapy
- The work of thesis
  - Moment invariant based texture analysis
    - Moment invariant based texture descriptors
    - The behavior of new texture descriptors
    - Graph cut based textured data segmentation
  - 3D prostate segmentation on T2 MRI
    - Prostate OSD segmentation
      - Adaptation to T2 MRI segmentation
      - Parameter tuning on the learning set of 33 cases
      - Evaluation of the influence of several statistical models
    - Multiple objects OSD framework
      - Automatic bladder segmentation
      - Rectum model
      - Introducing of anatomical information

    Robust T2 MRI segmentation framework
  - Surface-to-surface registration between TRUS and T2 MR volumes
    - Framework using a rigid transformation and a demons based elastic registration

Thank you!