

Some Successes and Challenges in Percutaneous Interventions

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Outline

- MRI guided prostate interventions
- Ultrasound guided liver ablation

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Transrectal Prostate Intervention Robot in Closed MRI Scanner

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E Atalar², LL Whitcomb¹, P Guion³, A Singh³,
C Menard⁴, J Coleman⁵

- 1 The Johns Hopkins University, Baltimore
- 2 Bilkent University, Ankara, Turkey
- 3 National Institutes of Health, Bethesda
- 4 Princess Margaret Hospital, Toronto, CA
- 5 Memorial Sloan Kettering Cancer Center, New York

Funding

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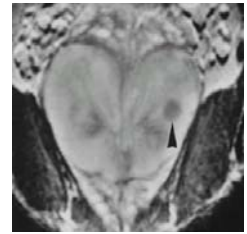
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Motivation – Prostate Cancer

- Over 1 Million prostate biopsies
- 230,000 new cases (annually in the U.S. alone)
- Will double by 2025

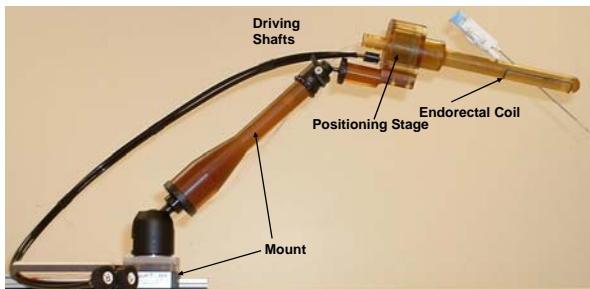
The MRI promise:

- Excellent sensitivity in detecting prostatic tissue abnormalities
- Ability of morphological, functional and molecular imaging
- May allow for “targeted biopsy”



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Our Approach – Robotic Assistant in Conventional MRI Scanner



- A. Krieger, R. Susil, C. Menard, J. Coleman, G. Fichtinger, E. Atalar, L. Whitcomb. Design of A Novel MRI Compatible Manipulator for Image Guided Prostate Interventions. IEEE Transactions on Biomedical Engineering, February 2005.

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Our Approach – Robotic Assistant in Conventional MRI Scanner

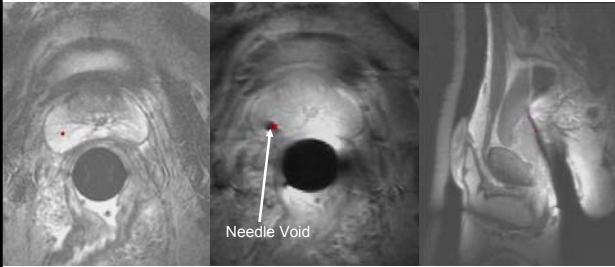


37 patients treated

- Ménard et al. An Interventional MRI Technique for the Molecular Characterization of Intra-Prostatic Dynamic Contrast Enhancement. Molecular Imaging, January-March 2005, 4(1): 63-66
- Susil et al., Transrectal Prostate Biopsy and Fiducial Marker Placement in a Standard 1.5T MRI Scanner, J Urol. 2006 Jan;175(1):113-20.

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Biopsy Example



MR Images during a clinical procedure:

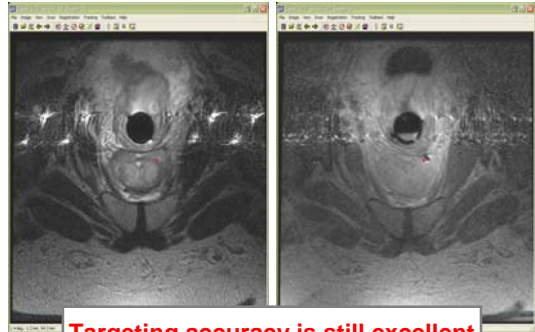
Left: A target (red dot) is selected on an axial TSE T2-weighted image.

Middle: The needle tip void is visualized in an axial TSE Proton Density image. The desired target matches the actual position of the needle.

Right: The needle void is visualized on a sagittal TSE Proton Density image, where the estimated needle path (red and purple dots) matches the actual path.

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Occasional Imaging Artifacts



Targeting accuracy is still excellent

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Real-time Tracking w/ Active Micro-coils



PROS

- High accuracy (0.2 mm and 0.3 degrees)
- High speed (20 Hz)
- Direct real-time tracking of the surgical tool (needle)

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Real-time Tracking w/ Active Micro-coils



CONS

- Custom tracking pulse sequence and data interface
- Occupies 3 channels (limits number of simultaneous imaging coils)
- Custom electronics is prone to failure (4 cases aborted)

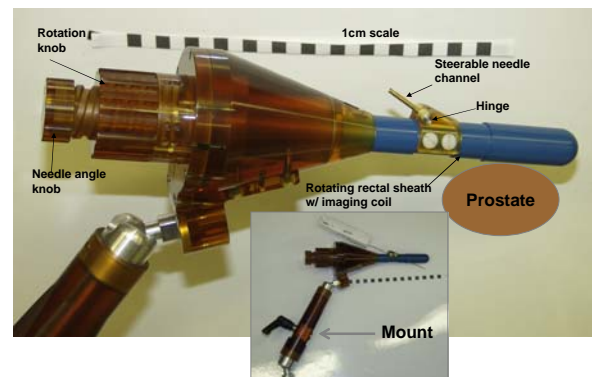
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New Objectives

- Independence from scanner
- Cheaply replicable
- No engineering support
- No custom electronics
- No pre-calibration
- Reduced imaging artifacts

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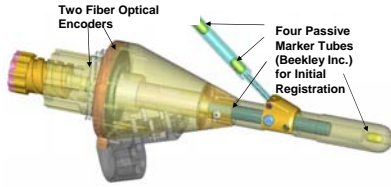
New Kinematics, Mechanics, and Mount



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6-DOF Hybrid Tracking

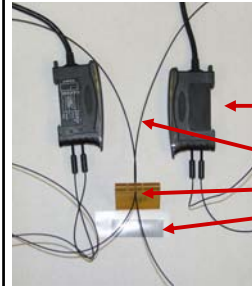
Homing: passive fiducials for absolute location of each robot joint
Incremental Motion: real-time incremental encoding of each joint



A Krieger, I Iordachita, G Metzger, P Guion, E Atalar, G Fichtinger, LL Whitcomb, Accuracy of Hybrid Tracking for a Novel MR-Guided Transrectal Prostate Interventional Device, 6th Interventional MRI Symposium, Leipzig, pp 143-145, 2006

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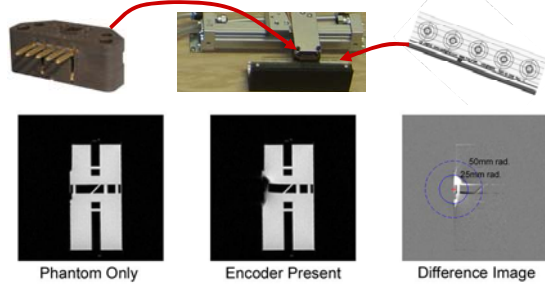
6-DOF Hybrid Tracking – Cheap Optical Joint Encoders (Rotation)



Banner fiber optic sensors (outside the scan room)
 0.25 mm plastic fiber in opposing style
 2 channel quadrature setup
 Resolution of 0.125 mm.

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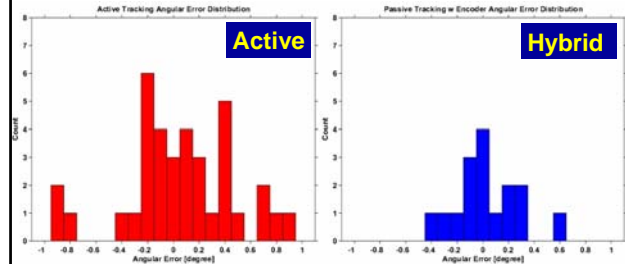
6-DOF Hybrid Tracking – Cheap Optical Joint Encoders (Translation)



Negligible imaging artifact at 50mm from isocenter (at 1.5T)

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Hybrid Tracking Error w/ New Robot



A Krieger, I Iordachita, G Metzger, P Guion, E Atalar, G Fichtinger, LL Whitcomb, Accuracy of Hybrid Tracking for a Novel MR-Guided Transrectal Prostate Interventional Device, 6th Interventional MRI Symposium, Leipzig, pp 143-145, 2006

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Summary of Recent Progress

- New robot & tracking scheme developed
- Errors compare favorably to existing methods
- Uses standard MRI pulse sequences
- Does not occupy any receiver channels
- Full MR compatibility
- Ease of deployment on different scanners
- FDA & IRB approvals obtained for trials
- Clinical trials at NIH in November, 2006
- System shipped to Princess Margaret Hospital

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Disclosures

none

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Collaborators

NCI

- Robert Grubb
- Ahmed Gharib
- David Thomasson
- Karen Ullman
- Peter Choyke

Johns Hopkins

- Robert Susil
- Csaba Csoma
- Siddharth Vikal
- Abdel-Monem El-Sharkawy
- Di Qian

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Ultrasound Monitoring of Tissue Ablation

Emad Bector¹, M. deOliveira², M. Choti²,
R. Ghanem¹, R. Taylor¹, G. Hager¹, G. Fichtinger¹

¹ Engineering Research Center (CISST ERC)
² Department of Surgery
Johns Hopkins University

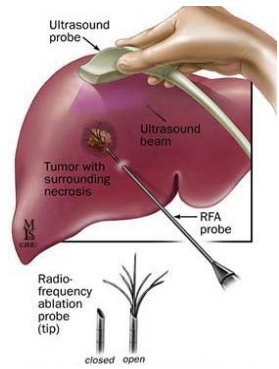
Funding

NSF EEC 9731478, Siemens Corporate Research

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Thermal Ablation of Liver Tumors

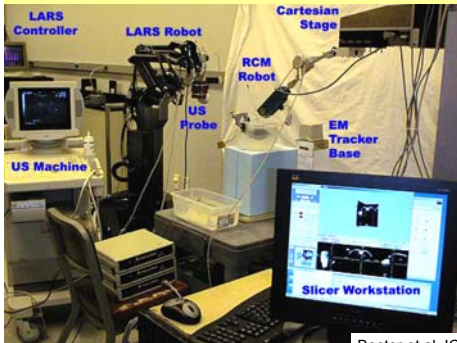
- 1M /year liver cancers worldwide
- The most frequent hepatic malignancy
- Surgical resection is the first choice
- Mixed treatments: unresectable liver tumors ablated under ultrasound guidance in the same open surgery



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Hopkins dual arm testbed

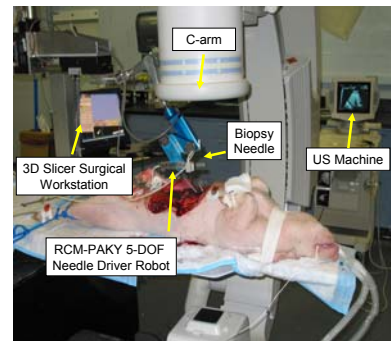
Testbed for calibration, control, and interventions



Bector et al. ICRA 2004

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In-Vivo Pig Experiment (2005)



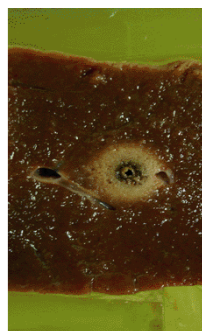
Bector et al. CARS 2005

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Ablation under US Guidance is Blind



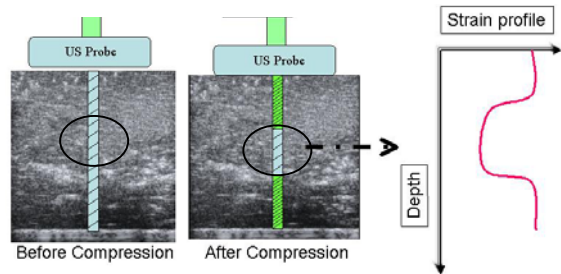
B-mode image



Gross-pathology

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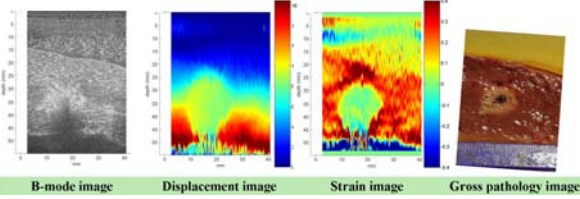
Changes of Stiffness – Strain Imaging (Pioneered by Ophir, Bamber, Varghese, etc.)



Before compression: Particles with uniform spacing
After compression: Two groups of particle spacing
 Differentiate axial displacement to yield axial strain (per continuum mechanics)
 Small spacing (green) → soft tissues moved more → high strain
 Large spacing (blue) → hard tissues move less → low strain

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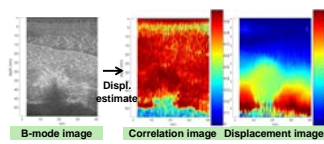
Limits of Conventional Strain Imaging



- Strain image can only approximate the ablated lesion
- Dynamic changes of tissue (gassing, charring, etc.) → aggressive changes in attenuation, shadowing, etc.
- Noisy US signal → Decorrelation noise → bad Displacement image
- Displacement to Strain least square differentiator amplifies the noise
- Hard to estimate Young's modulus from strain alone (stress is not uniform under the probe)
- 2D only
- Tends to be inconsistent even under extreme care

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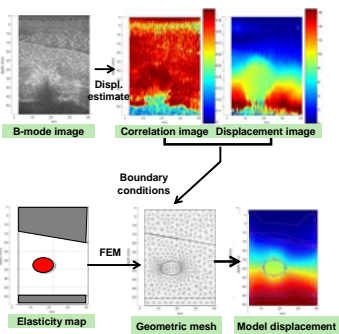
Elasticity-based Segmentation



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Boctor et al. MICCAI 2005

Elasticity-based Segmentation

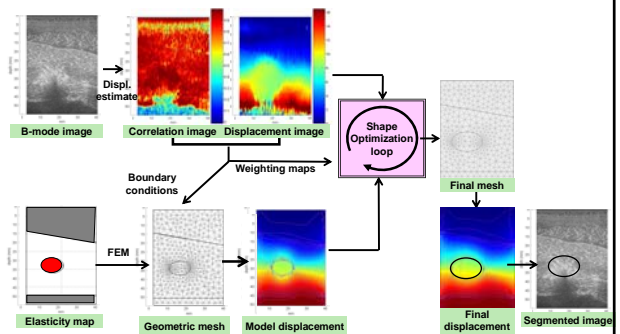


$$\rho \frac{\partial^2 u}{\partial t^2} - \nabla \cdot c \nabla u = K \quad \text{Navier's equation}$$

Boctor et al. MICCAI 2005

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Elasticity-based Segmentation

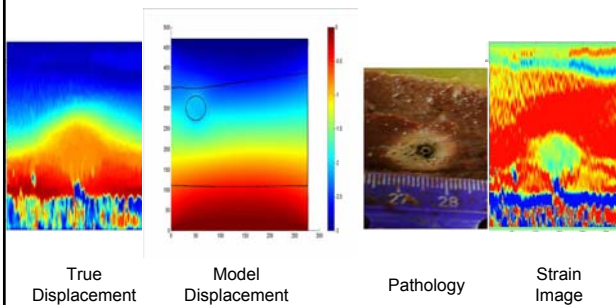


$$\hat{S} = \arg \min \{ \mathfrak{J}(S) = \sum_{i=1}^N \sum_{j=1}^M W(i, j) \| \hat{u}(i, j) - u(i, j; S) \|^{L1} \}$$

Boctor et al. MICCAI 2005

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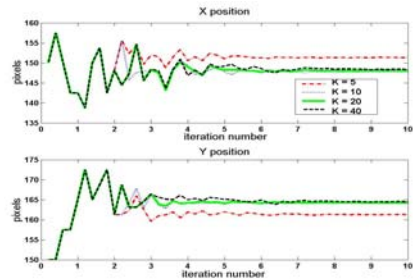
Segmentation Example



Boctor et al. MICCAI 2005

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Convergence Results



- Convergence error is within a few pixels
- K is the ratio of Young's modulus of cooked and normal liver
- 20 (green curve) is the correct value (literature & our own measurement)
- Robust to large errors in estimating K (between about 10 & 40)

Boctor et al. MICCAI 2005

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Overlapping Tumors & Burns

Large Tumor with Small Ablation Zone
Irregular Shaped Lesions

FEM model → Final mesh → Final displacement → Segmented image

Boctor et al. MICCAI 2005

3D Segmentation

Series of 2D FEM models → Solid 3D FEM model

Initial guess → Final Segmentation

Boctor et al. MICCAI 2005

Ultrasound Speckle Detection

- Each pixel is formed by the back scattered echoes from an approximately ellipsoid called the resolution cell.
- Such a summation of backscatters results in a granular image.
- Although of random appearance, speckle pattern is identical if the same object is scanned under the same focusing, frequency and direction.
- If each resolution cell has a number of scatterers more than 10 which are placed uniformly, a fully developed speckle is formed by definition.

A resolution cell Bovine liver

$$R = \frac{\langle A^{*R} \rangle}{\sigma_R} \quad S = \frac{\langle (A^{*S} - \langle A^{*S} \rangle)^2 \rangle}{\sigma_S^2} \quad \sigma_v^2 = \langle A^{2v} \rangle - \langle A^v \rangle^2$$

Data A is obtained in simulation by summing μ vectors (no. of scatterers) of length $\sqrt{2/\mu}$, i.e. random walk, and a vector of length k (coherency)

FS, CS, FDS

Rivaz et al. IEEE US Symposium, Vancouver, 2006

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FS, CS

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Rivaz et al. IEEE US Symposium, Vancouver, 2006

Ultrasound Calibration

$$\begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} = cT_2 \quad T_R \quad R \quad T_P \quad \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix}$$

$${}^wT_1(x, y, z, \alpha, \beta, \gamma) = \begin{pmatrix} \cos \alpha \cos \beta & \cos \alpha \sin \beta \sin \gamma - \sin \alpha \cos \gamma & \cos \alpha \sin \beta \cos \gamma + \sin \alpha \sin \gamma & x \\ \sin \alpha \cos \beta & \sin \alpha \sin \beta \sin \gamma + \cos \alpha \cos \gamma & \sin \alpha \sin \beta \cos \gamma - \cos \alpha \sin \gamma & y \\ -\sin \beta & \cos \beta \sin \gamma & \cos \beta \cos \gamma & z \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\mathbf{0} = \mathbf{f}(\theta, \phi) \approx \mathbf{f}(\theta, \phi_2) + \frac{\partial \mathbf{f}(\theta, \phi_2)}{\partial \phi} (\phi - \phi_2)$$

$$\Rightarrow \Delta \mathbf{f} = \mathbf{J}(\phi - \phi_2) = \mathbf{J} \Delta \phi$$

$$\phi_{2+1} = \phi_2 + (\mathbf{J}^T \mathbf{J} + \epsilon \mathbf{I})^{-1} \mathbf{J}^T \Delta \mathbf{f}$$

Prager RW, Rohling RN, Gee AH, Berman L. Rapid Calibration for 3-D Freehand Ultrasound. US in Med. Biol. 24(6):855-869, 1998
Mercier L, Lango T, Lindseth F, Collins DL. A review of calibration techniques for free-hand 3-D ultrasound systems. Ultrasound Med Biol. 2005;31(4):449-471.

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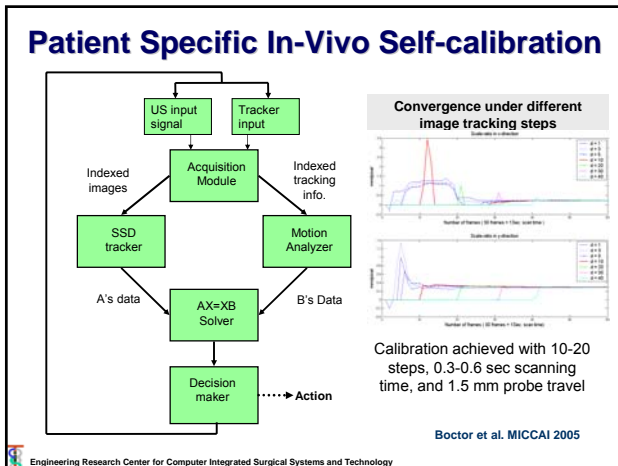
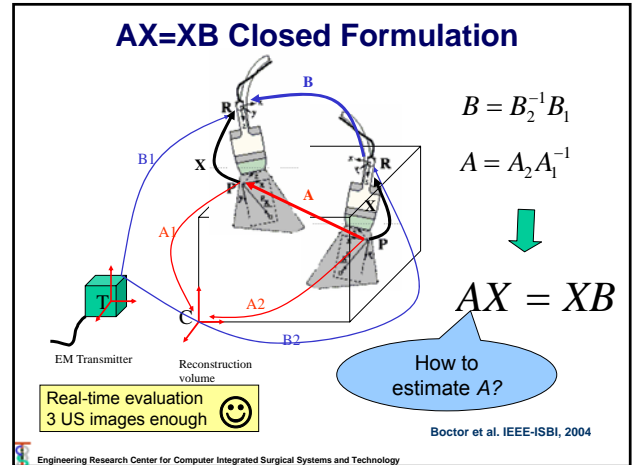
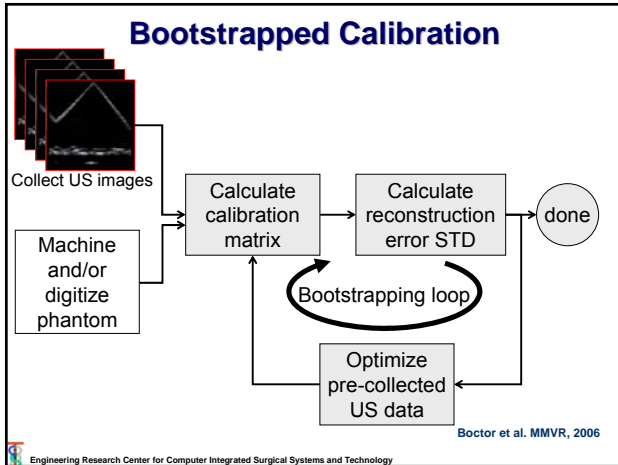
Conventional Workflow

Collect US images → Calculate calibration matrix → Calculate reconstruction error STD → done

Machine and/or digitize phantom

Linear pipeline → residual error
• Needs large number of images
• Slow non-linear optimization

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Disclosures
none

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