Catheter Based Interventions

...for Heart Valve Treatment

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Agenda

- Clinical Management of Heart Valve Patients
- Machine Learning in Medical Imaging
- Valve Modeling and Analysis
- Pre-op and Intra-op Data Fusion
- Therapy Modeling and Simulation
- Technology at Work in the Hybrid OR
Open heart surgery… an extremely invasive procedure

- General anesthesia
- Sternotomy
- Cardiopulmonary bypass
- Neurological damage
- Post-procedural complications
- Long recovery period
Cather based intervention … a less invasive alternative

- Instruments and devices are delivered through intravascular catheters
- Procedure executed under betting heart
- Local anesthesia and reduced trauma

Transfemoral :  

Transapical :  

Edwards SAPIEN Transcatheter Heart Valve - Edwards Lifesciences
Antegrade valve placement of the aortic valve prosthesis
Transcatheter Aortic Valve Implantation - TAVI

Exact valve placement with contrast agent and imaging control
Valve implantation exactly in the annulus
Final results, function assessment:
Valve Imaging and Analysis is HOT... and it is just the beginning

- Valve stenosis and regurgitation affect 2.5% of the global population and cause 60,000 deaths annually in the US.
- 100K valve replacement and repair procedures in the US – $141K per procedure and 4.9% in-hospital death rate
- Interventional / Minimal-Invasive mitral procedures are emerging – TAVI, E-Valve, Neochord + numerous startups
- Transcatheter aortic procedures are proliferating – successful 1-year outcome of the PARTNER trial => revolution in valve treatment
- Surgical planning and procedure navigation are new use cases – Planning software / Hybrid OR

Sources: ACC/ESC Clinical Guidelines
Current Clinical Management is Complex and Expensive

Cardiology
Radiology

Diagnosis
Follow-up
Medication
Additional Investigations
Invasive Treatment

Surgery
Cardiology
Anesthesiology

Planning
Open Heart Replacement
Open Heart Repair
Minimal Invasive (Robotic)

Guidance
Annular Support Devices
Edge-to-Edge Clipping Device
Coronary Sinus Devices
Left Atrial Devices

Clinical Relevant Information

- Etiology (prolapse/infection/calcium)
- Severity (mild/moderate/severe)
- Function (EF/Volume/Mass)
- Anatomical dimensions (valvular/annular)
- Hemodynamics (Pressure/Gradients)

- Procedure Timing
- Patient / Treatment Selection
- Anatomy/Dynamics Analysis
- Risk Stratification
- Treatment Outcome

- Devices/Instruments position
- Access paths visualization
- Target anatomy visualization

Current Disadvantages

- Time Consuming (Manual)
- Potential Inaccurate (Semiquantitative)
- Not Reproducible (User Dependent)
- Isolated Anatomical Assessment
- Limited Data (2D Imaging)

- Incomplete Anatomical/Dynamical Data
- Procedures Selection based on Surgeons Experience
- Limitations in Treatment Outcome Evaluation
- Limitations in Risk Assessment
- Repair procedure only in high profile centers

- Insufficient Visual Input (relevant Anatomies / lesions / devices)
- Image Artifacts from Devices
- Low correlation to planning data
- Risk for Complications
- Risk for Re-operation

Sources: ACC/ESC Clinical Guidelines

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The MICCAI Perspective...

- **Goal**: Process images into clinical relevant information
- **Problems**: object detection, segmentation – modeling, registration – fusion, and tracking
For most of the medical imaging problems:

- Accurate knowledge is absent and right answer subjective
- The problem is difficult to model
- Solution needs to be robust wrt to patients, pathology, image quality, etc.
- Solution needs to be obtained in reasonable time

Machine Learning uses statistical methods to learn from examples and find approximate solutions for the above challenges.

Large databases of medical images have become available in the recent years, as a result of the proliferation of cost-effective non-invasive imaging techniques.
Knowledge-Driven Learning Platform for
Fast and Accurate object localization and motion estimation

Core Technology for:
• Database-Guided Anatomical Structure Detection;
• Multimodal Tracking using Robust Information Fusion;
• Database-Guided Non-rigid Shape Inference
• Database-Guided Quantification

Annotated Medical Image Databases (2D, 3D, 4D)


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Creating the Training Set using the “Undergraduate Student Technique”

- Define the geometrical / anatomical model
- Use adequate editing and viewing methods
- Use iterative, semi-automatic process to speed up annotation
- Use experts to review and improve annotation quality
- 100+ patients decent performance, 500+ robust performance
Extracting Statistics using Image Features

- Use computational efficient features with discriminative power
- Haar-Features and Integral Image for efficient over complete representation (Papageorgiou ‘98, Viola - Jones ’01)
- Steerable Features and Local-Spatio-Temporal Features – aligned to spatial and temporal parameters
- Extension to three dimensional problems straightforward
Combining Weak Predictors into Strong Classifiers

Final classifier is linear combination of weak classifiers

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Learning the Posterior Distribution using PBT

- Divide and Conquer strategy to learn a tree of strong classifiers
- Recursively separate positives from negatives
- Focus on ambiguous samples
- Final posterior aggregate from descendents
- Better convergence performance compared to AdaBoost
Testing Hypotheses

- Example: Location of the Aortic Valve in CT slices
- Discretize parameter search space to obtain (x,y) hypotheses
- Scan learned detector exhaustively over all hypothesis to obtain probability distribution
- Aggregate most probable candidates to construct final result
Marginal Space Learning solves pose estimation in 3D images

\[ \arg\max_x p(x|I) = \arg\max_x D(x, I), \ x \in \Sigma \]

\[ \text{dim}(x) = 9 \quad |\mathcal{H}| = 10^9 \quad \Rightarrow \text{Huge Space} \]

- Space Marginalization, train and detect in sub-space with increased dimensionality

\[ \Sigma_1 \subset \Sigma_2 \subset \cdots \subset \Sigma_n = \Sigma \]

\[ \text{dim}(\Sigma_1) \ll \text{dim}(\Sigma) \]

- Marginal space for similarity transform

\[ \Sigma_1 = (c_x, c_y, c_z) \]

\[ \Sigma_2 = (c_x, c_y, c_z, \alpha_x, \alpha_y, \alpha_z) \]

\[ \Sigma_3 = (c_x, c_y, c_z, \alpha_x, \alpha_y, \alpha_z, s_x, s_y, s_z) \]

- Train multiple detectors

\[ p(\theta(t)|I(t)) = p(c_x, c_y, c_z|I(t)) \]

\[ p(\alpha_x, \alpha_y, \alpha_z|c_x, c_y, c_z, I(t)) \]

\[ p(s_x, s_y, s_z|\alpha_x, \alpha_y, \alpha_z, c_x, c_y, c_z, I(t)) \]

! Robust and fast solution for 3D problems

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Trajectory Spectrum Learning solves object detection in 4D (3D+t) images

\[
\arg \max_{I, \theta} p(I, \theta) = \arg \max_{I, \theta} p(I(0), \cdots, I(n-1), \theta(0), \cdots, \theta(n-1))
\]

=> Tracking by Detection (MSL) produces noisy motion patterns

- DFT decomposition of the trajectory
  \[
  \tilde{s}^j(f) = \sum_{t=0}^{T-1} \tilde{I}^j(t) e^{-j2\pi tf}
  \]

- Formulate the problem in the compact trajectory spectrums – orthogonal subspace

\[
\arg \max_{s^j} p(s^j | I, \theta) = \arg \max_{s^j} p(s^j(0), \cdots, s^j(T-1) | I(0), \cdots, I(n-1), \theta(0), \cdots, \theta(T-1))
\]

! Robust solution for 3D+t problems
Incremental Estimation of Patient-Specific Parameters from Cardiac Images

- Probabilistic Boosting Tree
- Marginal Space Learning
- Haar- and Steerable Features
- RANSAC

Global Location and Rigid Motion Estimation
\[ \theta(t) \]

Non-Rigid Landmark Motion Estimation
\[ \vec{a}_i^j(t) \]

Non-Rigid Shape Estimation
\[ M(t) \]

Input volume sequence over one cardiac cycle

Patient-Specific Modeling of the Aortic and Mitral Valve from TEE and CT - Pathologies
Patient-Specific Modeling of the Heart Valves from Multi-modal Images: Diagnosis and Planning

CT (Syngo.via VA11)  DynaCT  US (SC2000)  MRI

2011 MICCAI Young Scientist Award
A Unified Heart Model to Analyze Anatomy and Dynamics from Multi-modal Cardiac Data

4D Echocardiography  Cardiac CT  Cardiac MRI

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• Focus on model completeness: valves, chambers, and great vessels
• Focus on physiological details: sub-valvular apparatus, clefts, scallops
Patient-Specific Modeling of the Heart Valves from Multi-modal Images: Diagnosis and Planning

Modeling and Analysis of Anatomy and Dynamics of the Heart Valves
- Automated estimation of location, anatomical landmarks and surface structures
- Intelligent Workflow-Guided Model Validation < 5min modeling time
- Comprehensive and reproducible quantification of anatomy and dynamics

Precise, Reproducible, Functional, Comprehensive Valvular Analysis – Cardiology / Anesthesiology
Physiological Modeling and Quantitative Planning of Heart Valve Surgery – Surgery / Inter-Cardiology
Fusion of Pre-operative and Intra-operative Data

- Detect Cardiac Structures in Pre-op Data (CT/TEE/MR)
  - Mitral Valve Anatomy, Left Ventricle, Pericardium
- Fuse Pre-op Models and Data with Intr-op Data
  - Robust detection of intra-op models and fusion of pre-op – intr-op data
- Overlay “Rich” Planning Information on Live Fluoro
  - C-arm angulations and instrument guidance

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Fusion of Pre-operative and Intra-operative Data

$$(\hat{\phi}, \hat{M}) = \arg \max_{M, \phi} \log (P(M | I_1) \cdot P(M | \phi(I_2)) \cdot P(M | I_1, \phi(I_2)) \cdot P(M, \phi | \mu, \Sigma))$$

- **Completeness** - by exploiting the complementary information from multiple modalities
- **Robustness** - by exploiting the redundant information from multiple modalities to reduce the estimation uncertainty
- **Fusion** - by obtaining a model-sensitive integration of the pre-operative and intra-operative modalities
Fusion of Pre-operative and Intra-operative Data

Model-Based Fusion of Multi-Modal Volumetric Images: Application to Transcatheter Valve Procedures

- Fusion approach improves model estimation accuracy
- Specifically the intra-op model accuracy is improved

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Physically-Constrained Modeling

Physically-Driven Step
Transformations $\Psi$ and $\phi$ estimated by solving dynamics equation (isotropic linear elastic\textsuperscript{5}, co-rotational finite element\textsuperscript{6}):

$$\dot{\mathbf{M}} \ddot{\mathbf{U}} + \mathbf{C} \dot{\mathbf{U}} + \mathbf{K} \mathbf{U} = \mathbf{F}_{\text{ext}}(\mathbf{v}_n^n) = -\mathbf{F}$$

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P7-186-T, Tuesday (Sept 20) 15:00-16:15

Robust Physically-Constrained Modeling of the Mitral Valve and Subvalvular Apparatus

$$\begin{align*}
S_{t_1} &= \arg \max_{\hat{S} \in \Omega} p(\hat{S} | I_{t_1}) \\
S_{t_2} &= \arg \max_{\hat{S} \in \Omega} p(\hat{S} | I_{t_2}) \\
S_{t_2} &= \phi(S_{t_1}) \text{ and } S_{t_1} = \psi(S_{t_2})
\end{align*}$$

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Towards Patient-Specific Finite-Element Simulation of MitralClip Procedure

- Simulation of valve closure with patient-specific anatomical and biomechanical parameters
- Simulation of E-valve clipping and artificial chords for optimal treatment decision

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Transcatheter valve procedures are “HOT” and require extensive imaging technology.

Machine Learning efficiently solves various problems in medical imaging.

Unified model of the heart across modalities / workflow

Using biomechanical models for patient-specific therapy simulation.
Questions ?