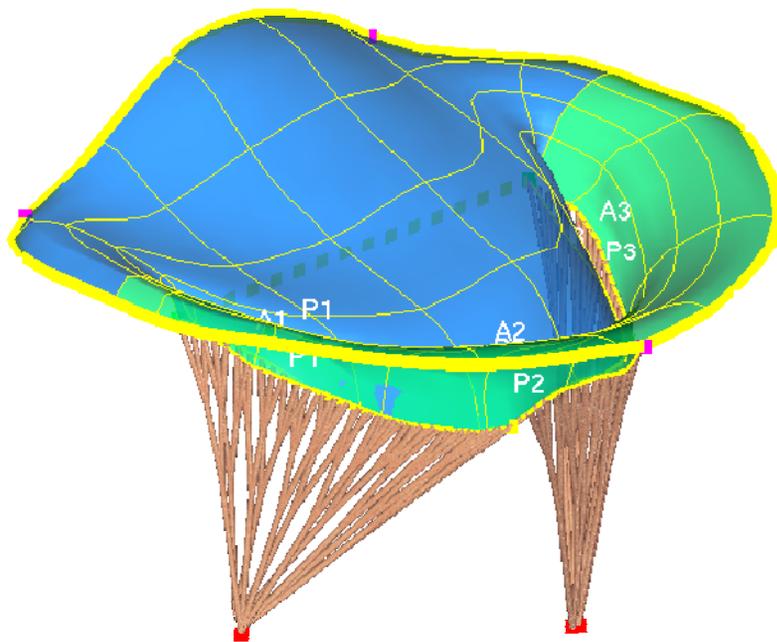


Catheter Based Interventions

...for Heart Valve Treatment



Razvan Ioan Ionasec

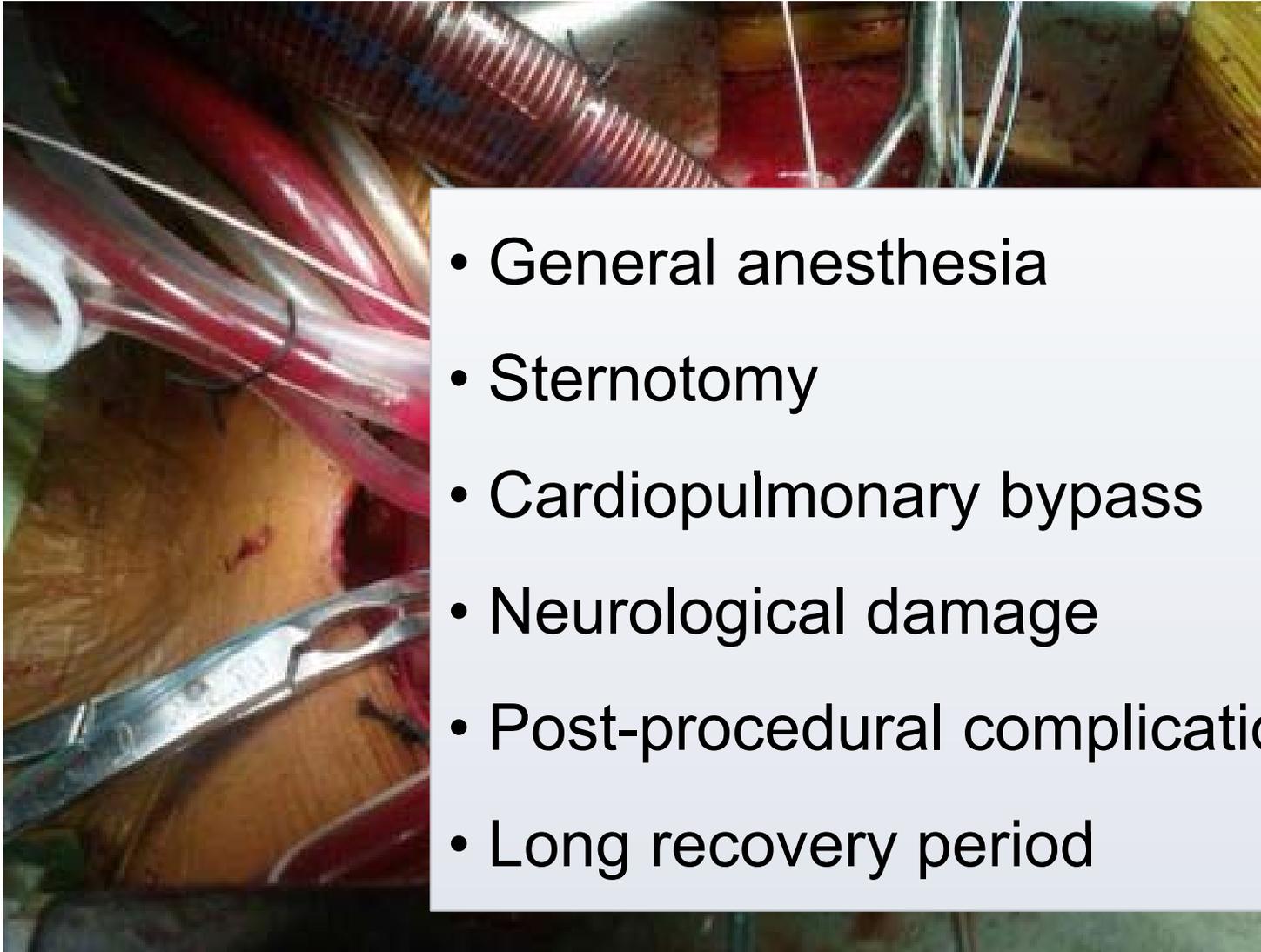
Image Analytics and Informatics
Siemens Corporate Research
Princeton, NJ

with contribution from colleagues: Ingmar Voig, Sasa Grbic, Dime Vitanovski, Kristof Ralovich, Tommaso Mansi, Yang Wang, Viorel Mihalef, Yefeng Zheng, Bogdan Georgescu and Dorin Comaniciu

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

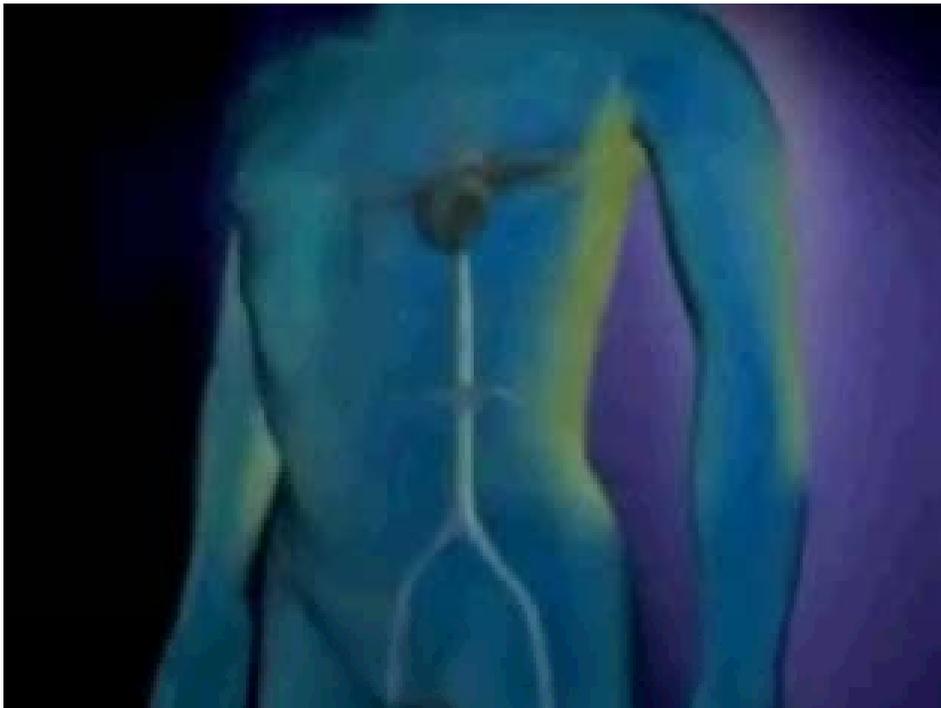


- General anesthesia
- Sternotomy
- Cardiopulmonary bypass
- Neurological damage
- Post-procedural complications
- Long recovery period

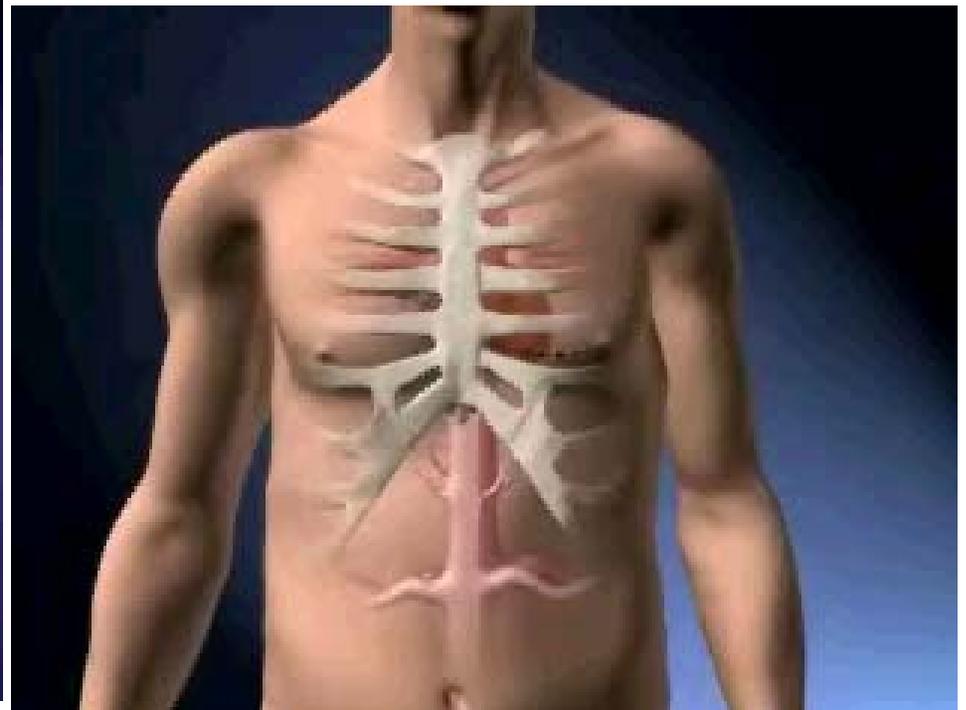
Cather based intervention ... a less invasive alternative

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

Transfemoral :



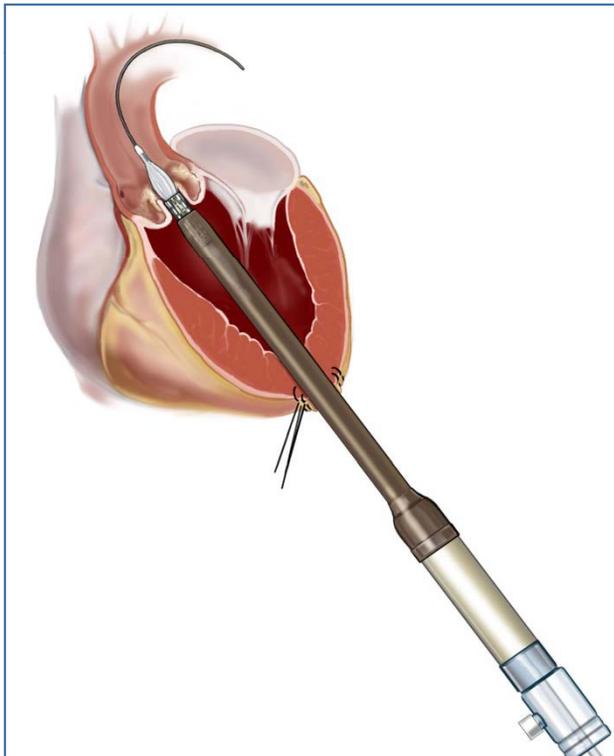
Transapical :



Edwards SAPIEN Transcatheter Heart Valve - Edwards Lifesciences

Transcatheter Aortic Valve Implantation - TAVI

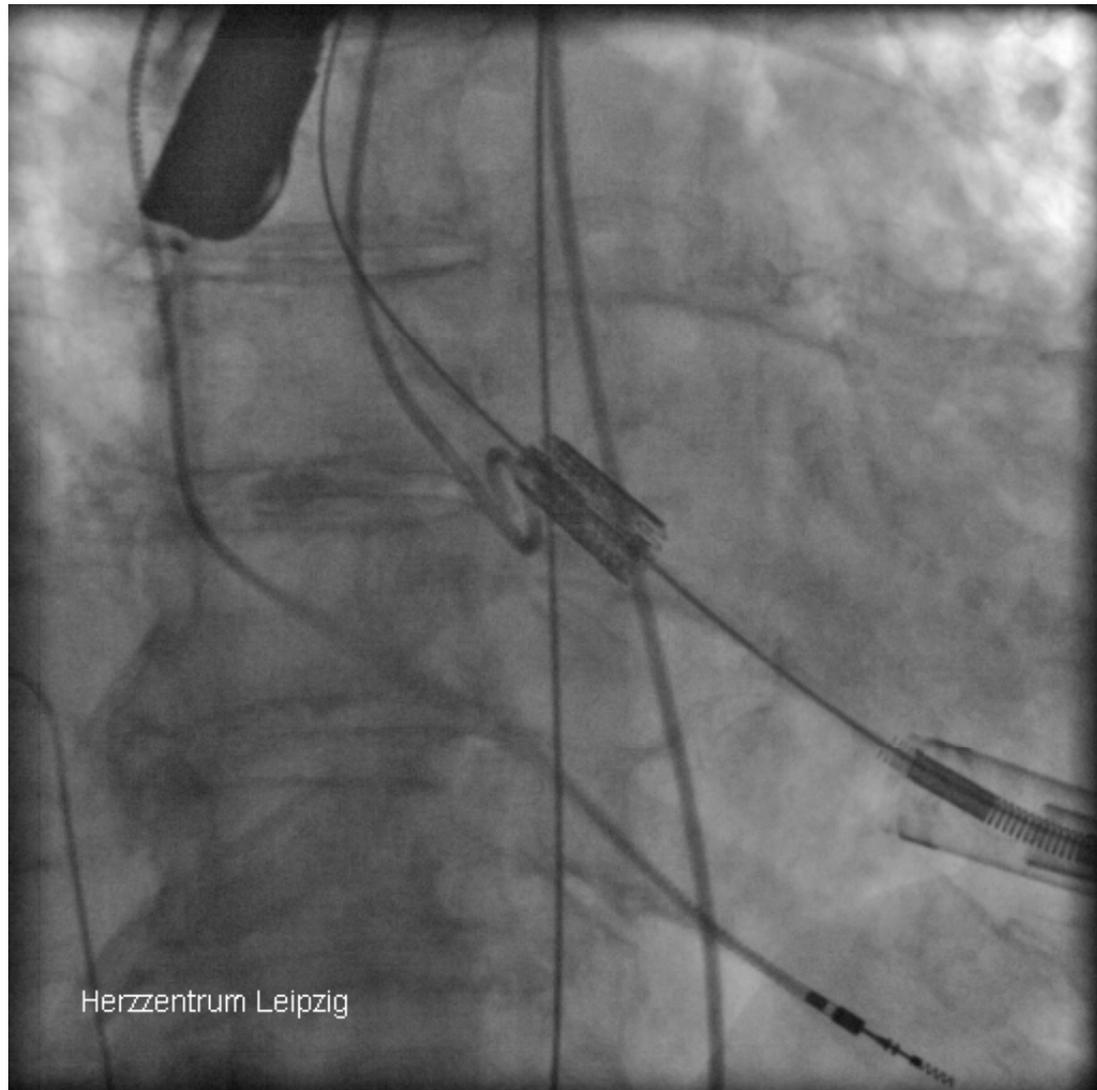
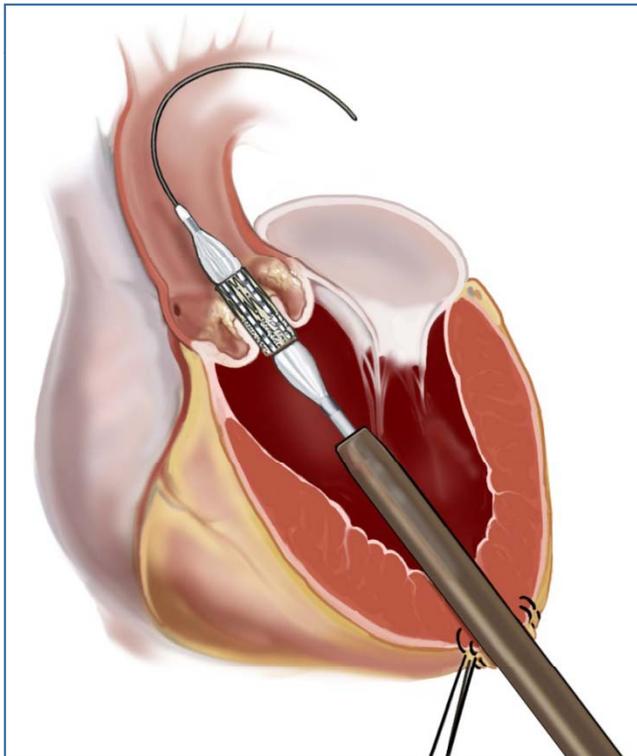
Antegrade valve placement
of the aortic valve
prosthesis



Herzzentrum Leipzig

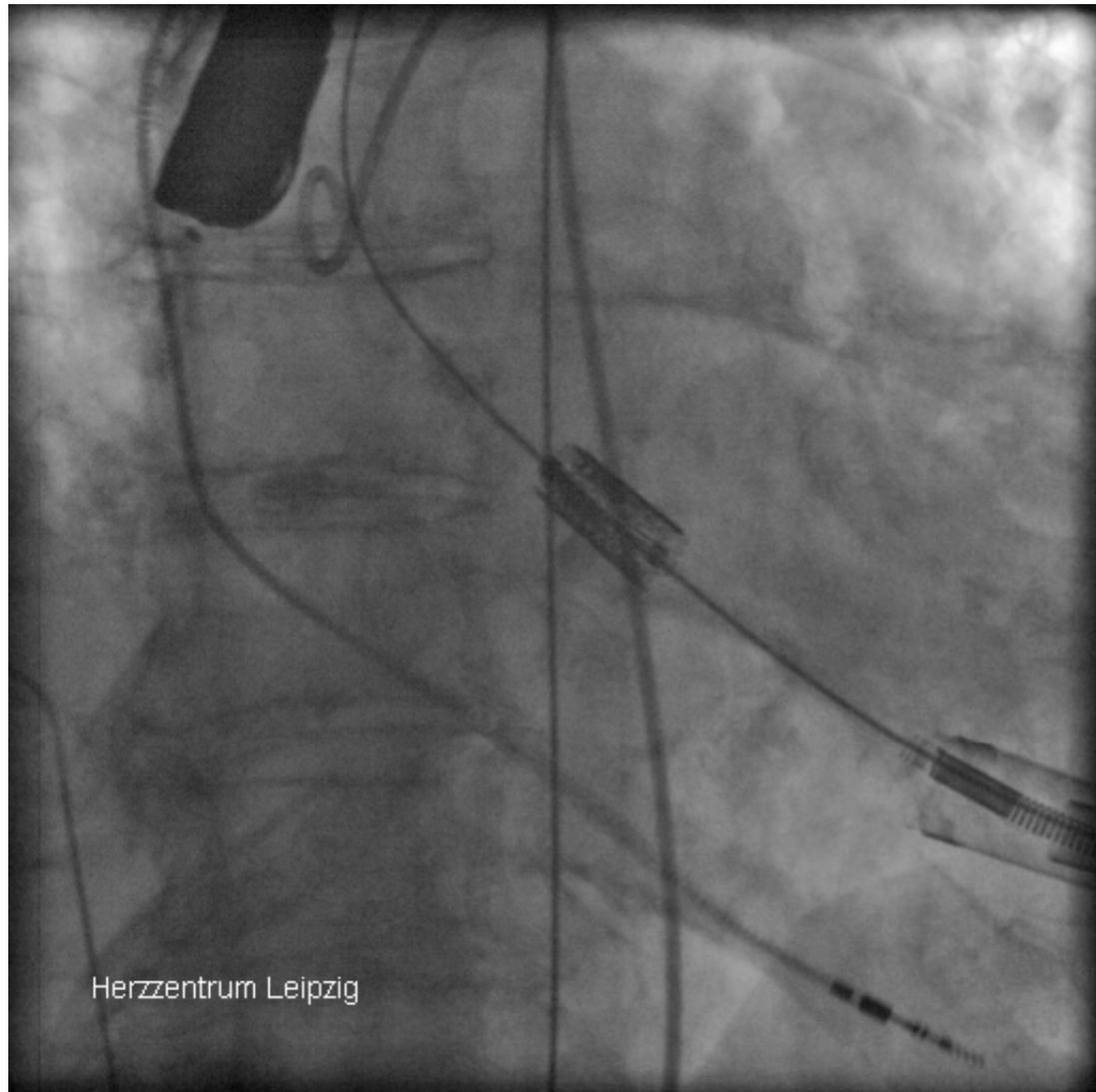
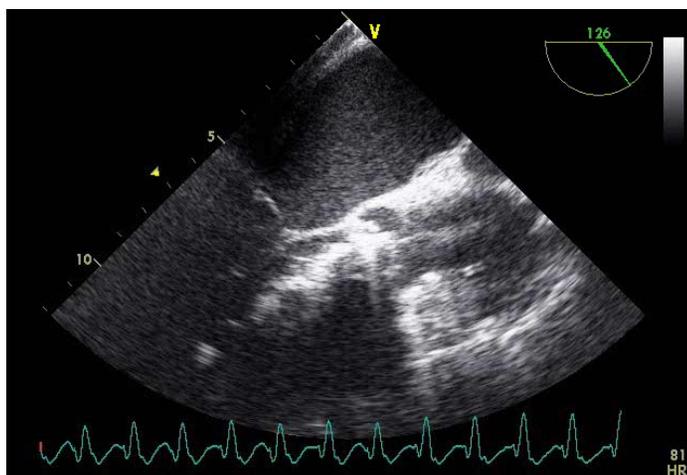
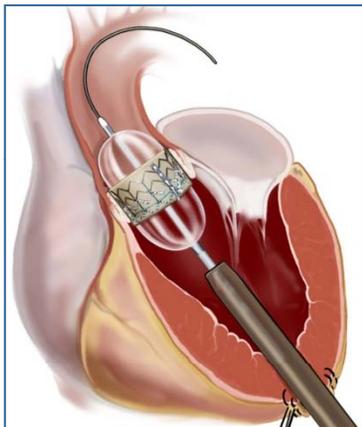
Transcatheter Aortic Valve Implantation - TAVI

Exact valve placement with contrast agent and imaging control



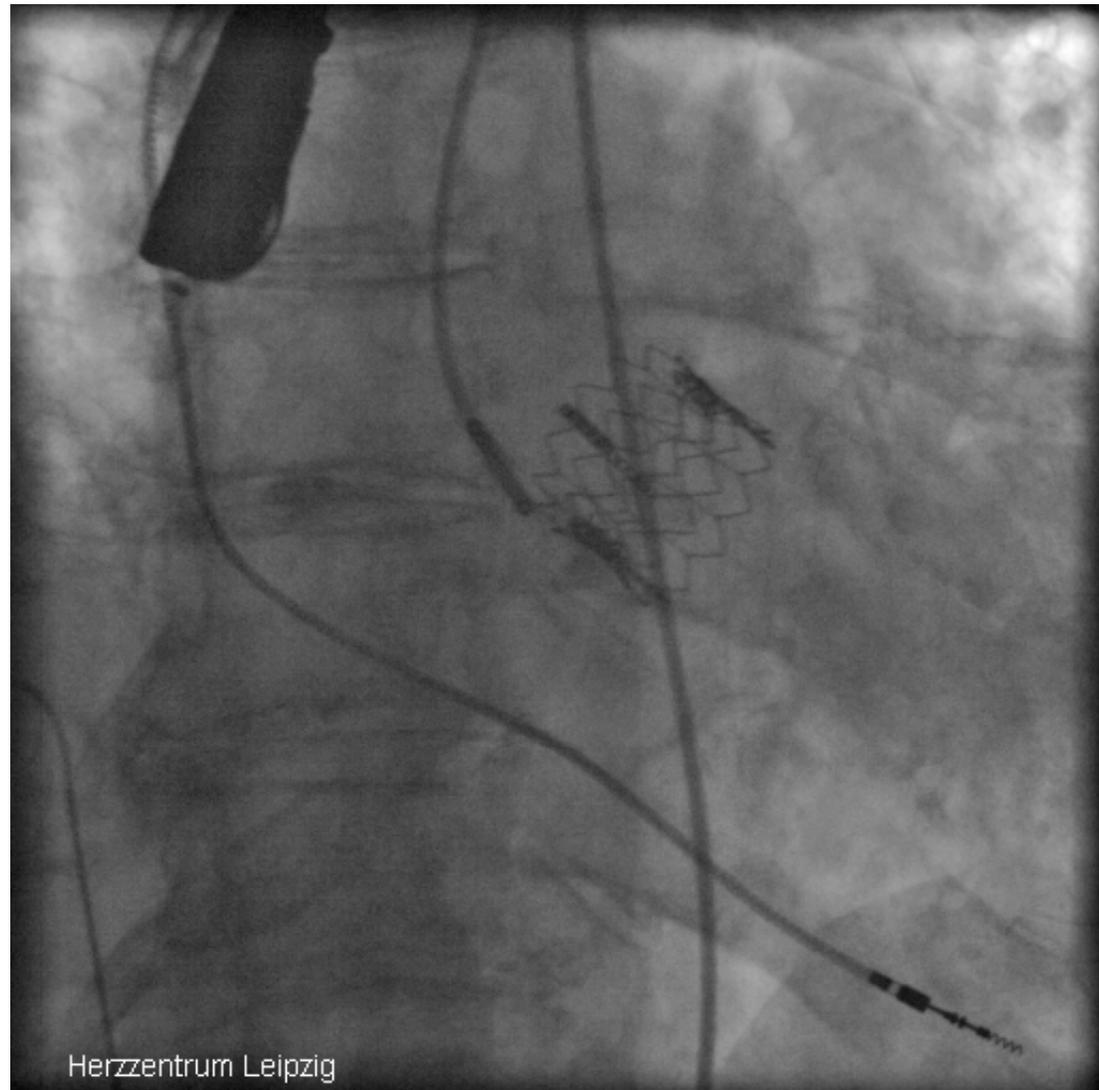
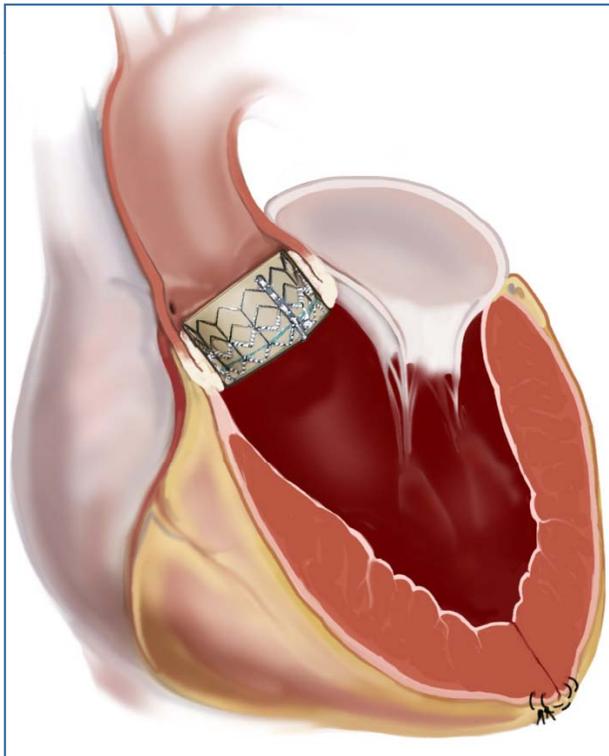
Transcatheter Aortic Valve Implantation - TAVI

Valve implantation exactly in the annulus

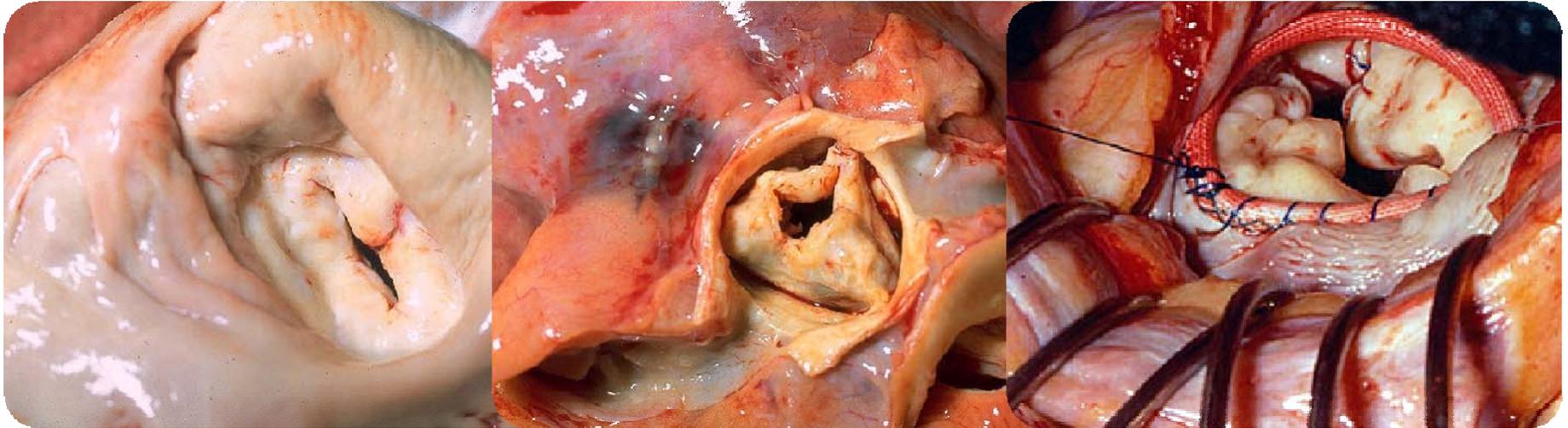


Transcatheter Aortic Valve Implantation - TAVI

Final results,
function assessment:



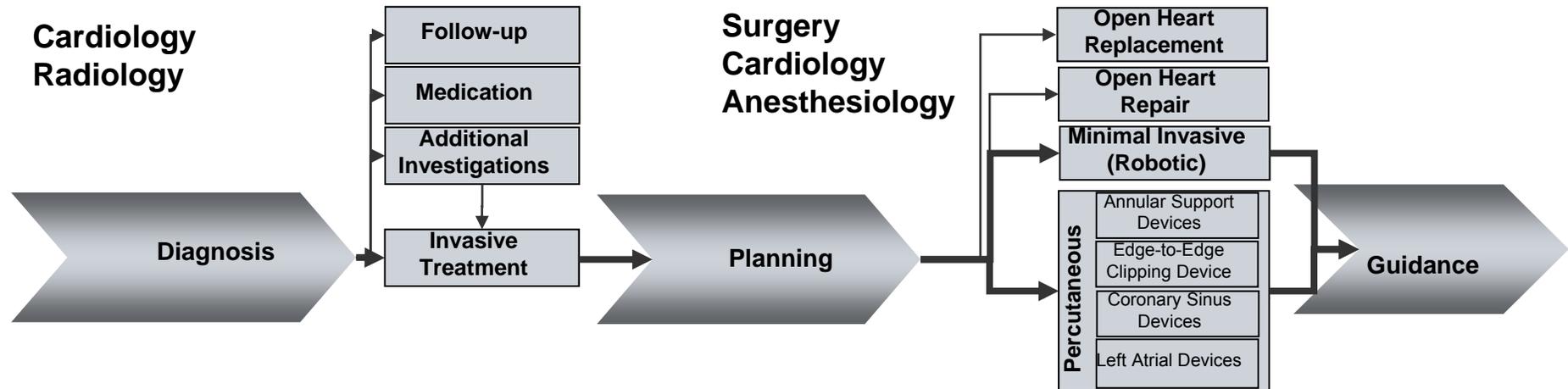
Valve Imaging and Analysis is HOT... and it is just the beginning



- 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



Clinical Relevant Information

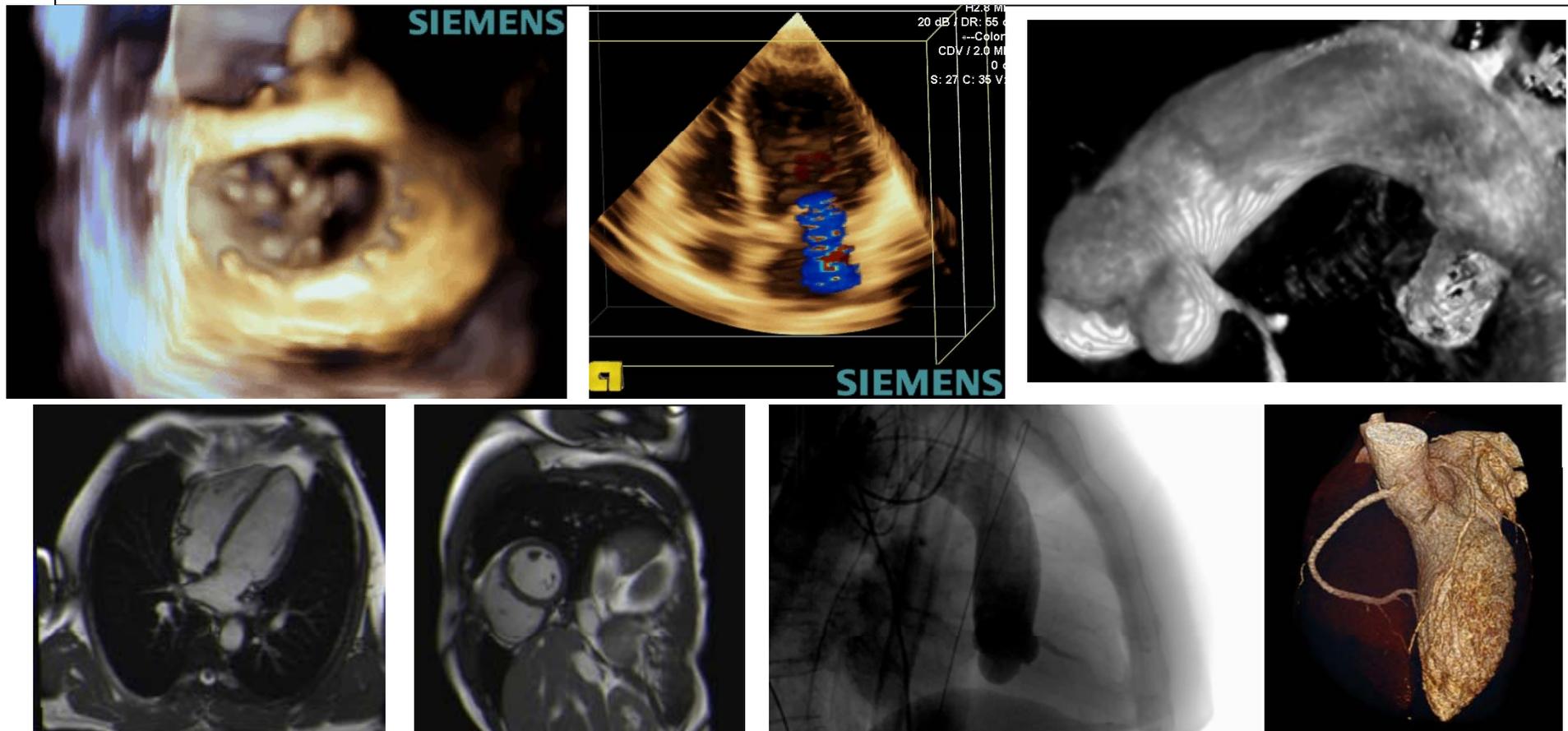
- Etiology (prolapse/infection/calcium)
- Severity (mild/moderate/severe)
- Function (EF/Volume/Mass)
- Anatomical dimensions (valvular/annular)
- Hemodynamics (Pressure/Gradients)
- Procedure Timing
- Patient / Treatment Selection
- Anatomy/Dynamics Analysis
- Risk Stratification
- Treatment Outcome
- 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

The MICCAI Perspective...



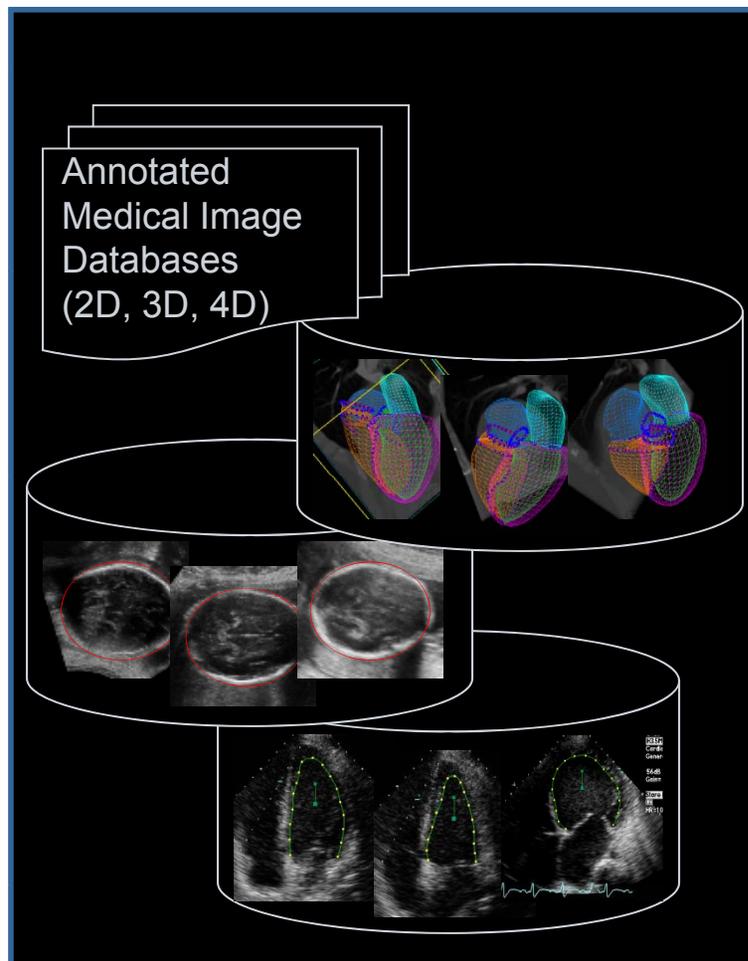
- **Goal:** Process images into clinical relevant information
- **Problems:** object detection, segmentation – modeling, registration – fusion, and tracking

Machine Learning in Medical Imaging

- **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.**

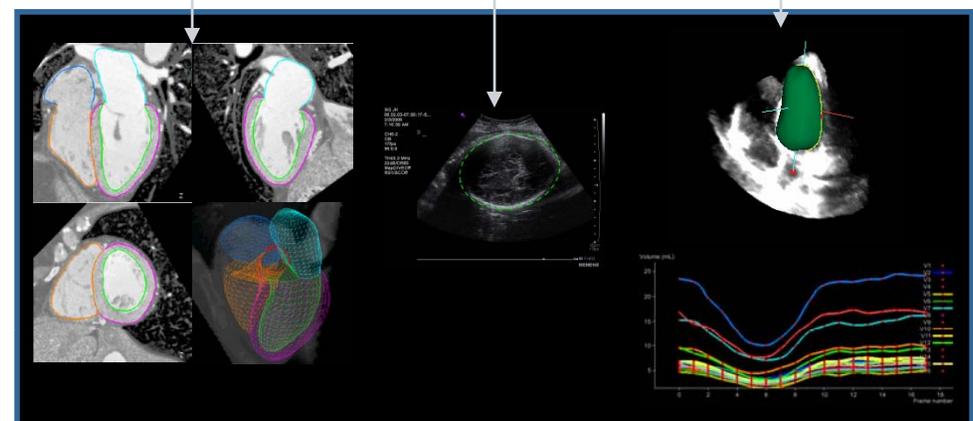
Knowledge-Driven Learning Platform for Fast and Accurate object localization and motion estimation

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Core Technology for:

- Database-Guided Anatomical Structure Detection;
- Multimodal Tracking using Robust Information Fusion;
- Database-Guided Non-rigid Shape Inference
- Database-Guided Quantification



Zheng et al. IPMI2009, TMI2008; Ionasec et al. ICCV2009; Yang et al. CVPR2008

Razvan I. Ionasec: razvan.ionasec@siemens.com

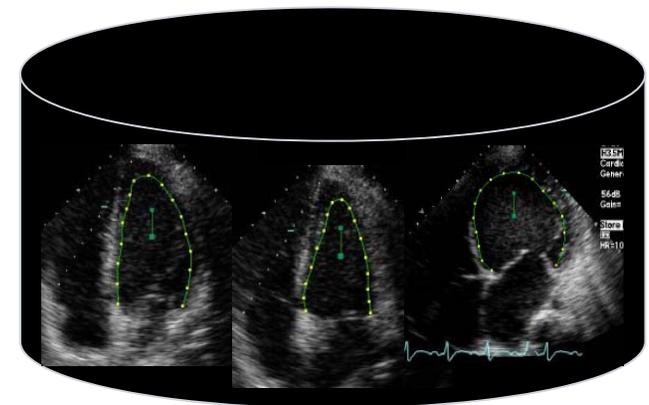
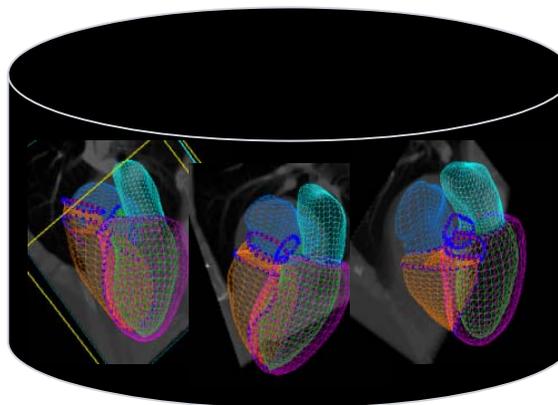
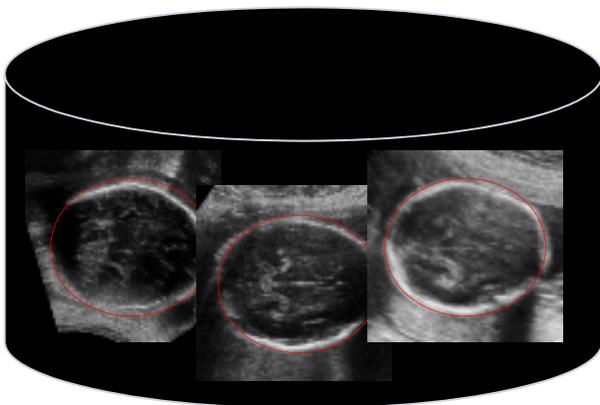
Sept. 2011

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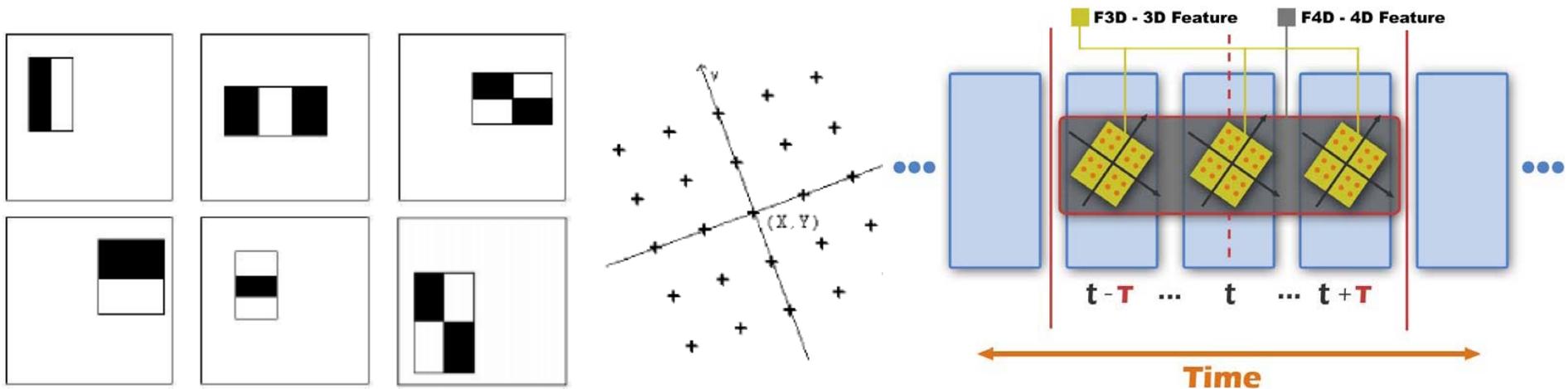
Creating the Training Set using the “Undergraduate Student Technique”

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

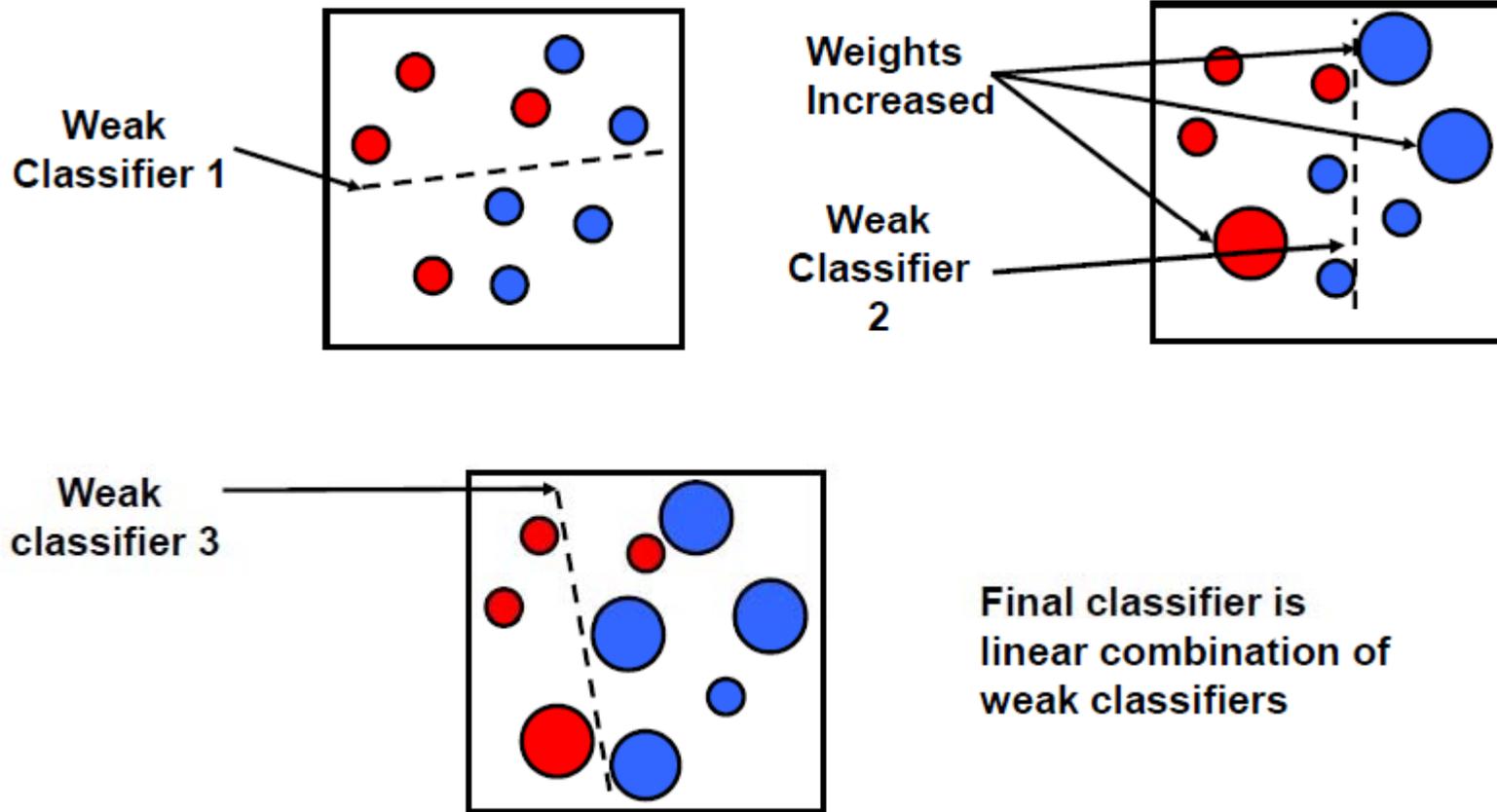


Extracting Statistics using Image Features



- 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

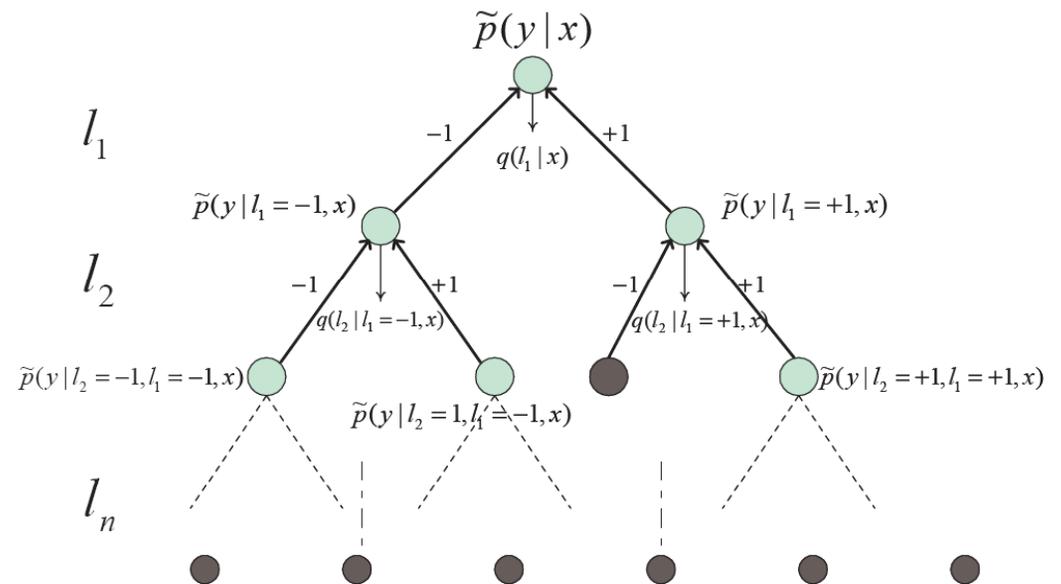
Combining Weak Predictors into Strong Classifiers



Picture Courtesy: Machine Learning Techniques for Computer Vision (ECCV2004), C. M. Bishop

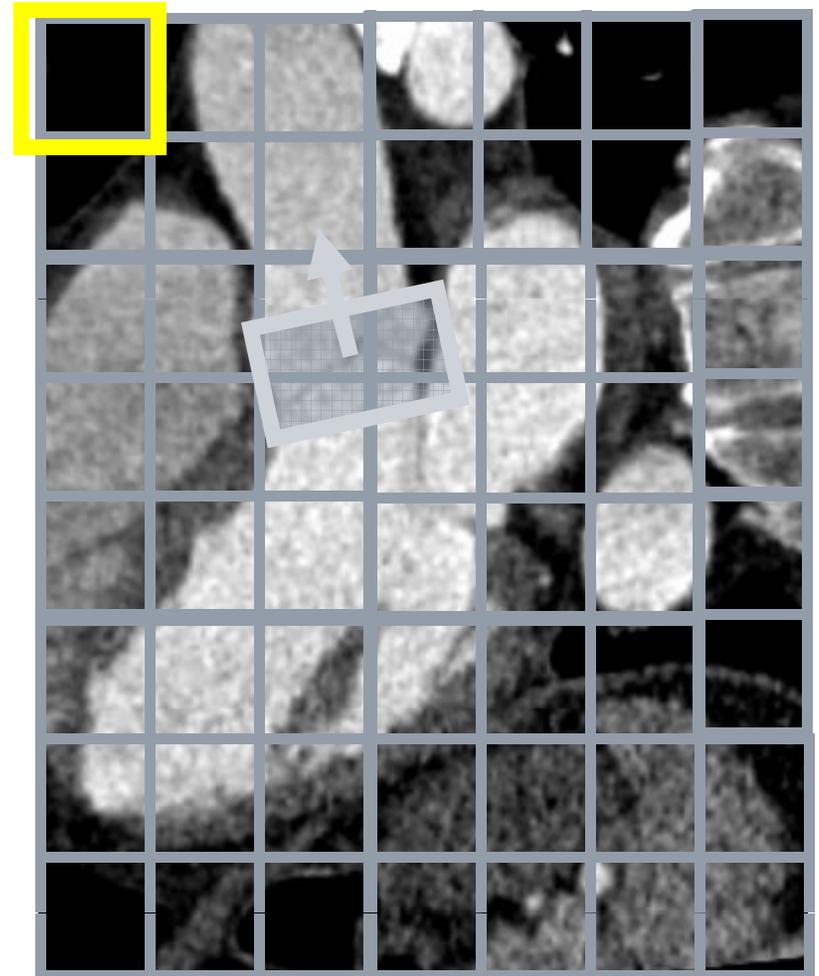
Learning the Posterior Distribution using PBT

- 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

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$$\operatorname{argmax}_x p(x|I) = \operatorname{argmax}_x D(x, I), x \in \Sigma$$

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

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

$$\Sigma_1 \subset \Sigma_2 \subset \dots \subset \Sigma_n = \Sigma$$

$$\dim(\Sigma_1) \ll \dim(\Sigma)$$

- Marginal space for similarity transform

$$\Sigma_1 = (c_x, c_y, c_z)$$

$$\Sigma_2 = (c_x, c_y, c_z, \vec{\alpha}_x, \vec{\alpha}_y, \vec{\alpha}_z)$$

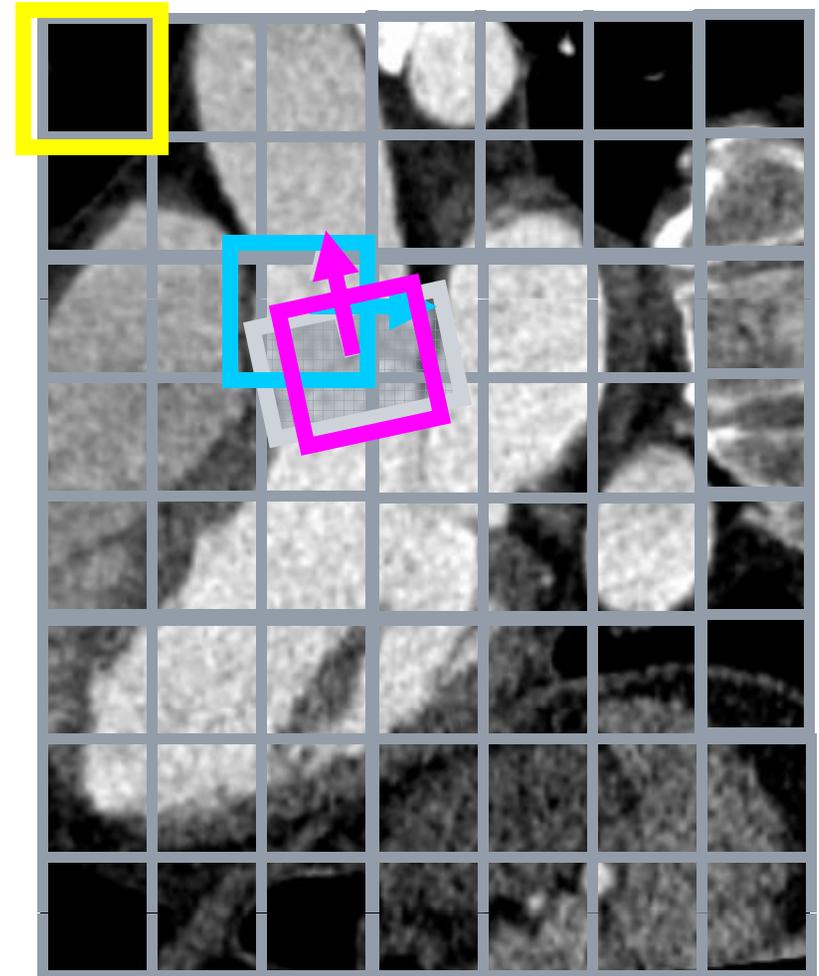
$$\Sigma_3 = (c_x, c_y, c_z, \vec{\alpha}_x, \vec{\alpha}_y, \vec{\alpha}_z, s_x, s_y, s_z)$$

- Train multiple detectors

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

$$p(\vec{\alpha}_x, \vec{\alpha}_y, \vec{\alpha}_z|c_x, c_y, c_z, I(t))$$

$$p(s_x, s_y, s_z|\vec{\alpha}_x, \vec{\alpha}_y, \vec{\alpha}_z, c_x, c_y, c_z, I(t))$$



! Robust and fast solution for 3D problems

2011 Thomas A. Edison Patent Award

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



$$\arg \max_{\vec{L}^j} p(\vec{L}^j | I, \theta) = \arg \max_{\vec{L}^j} p(\vec{L}^j(0), \dots, \vec{L}^j(n-1) | I(0), \dots, I(n-1), \theta(0), \dots, \theta(n-1))$$

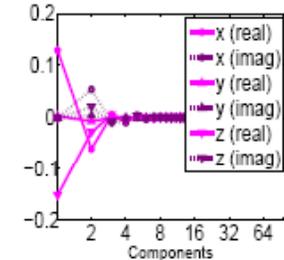
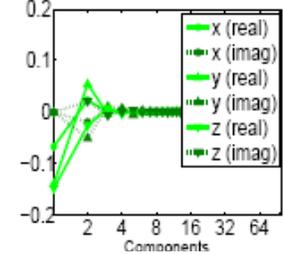
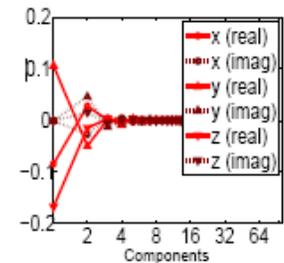
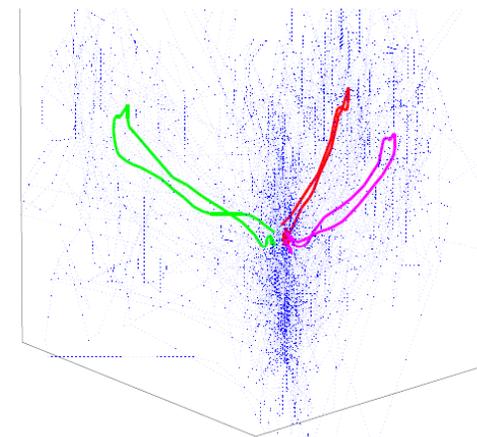
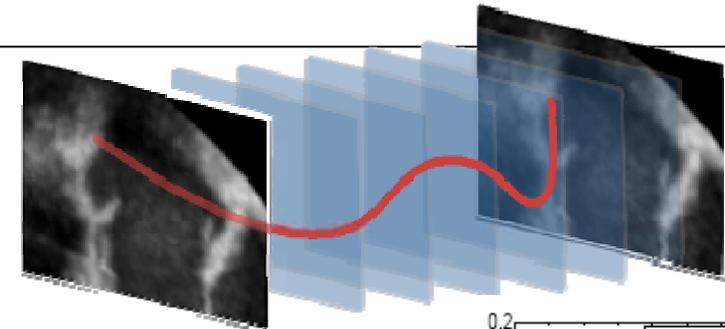
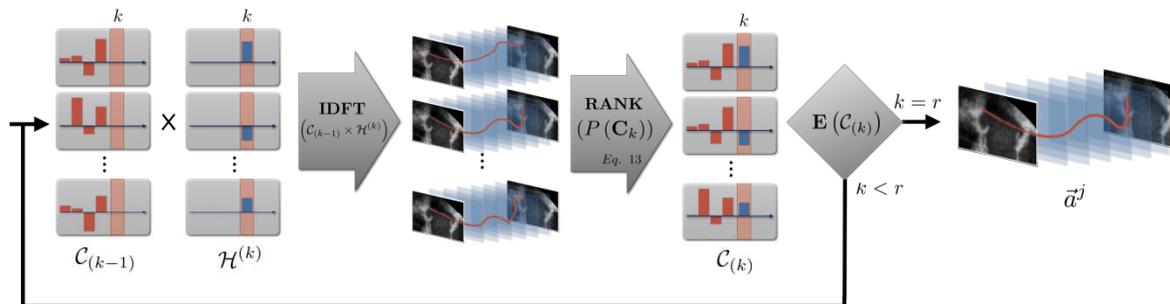
=> Tracking by Detection (MSL) produces noisy motion patterns

- DFT decomposition of the trajectory

$$\vec{s}^j(f) = \sum_{t=0}^{T-1} \vec{L}^j(t) e^{-\frac{j2\pi t f}{T}}$$

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

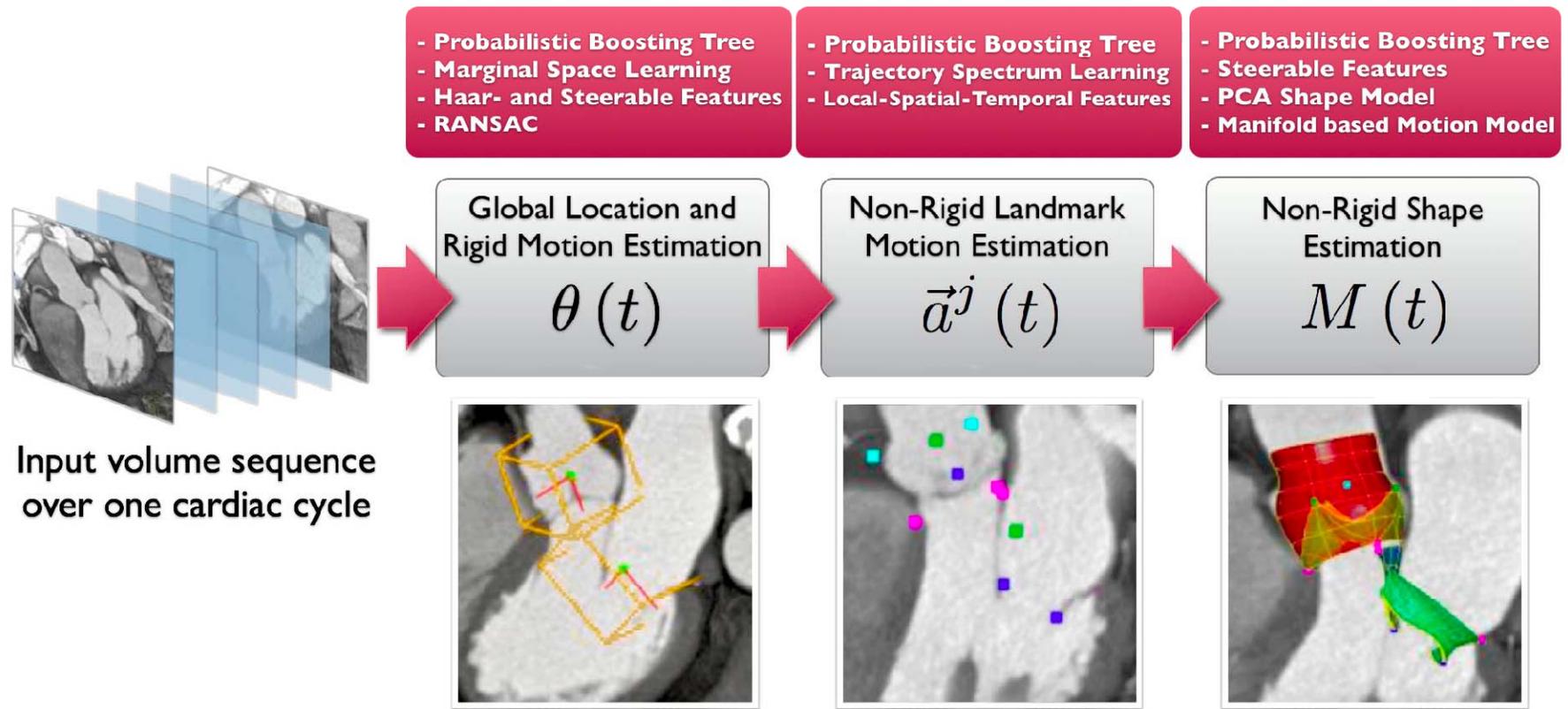
$$\arg \max_{\vec{s}^j} p(\vec{s}^j | I, \theta) = \arg \max_{\vec{s}^j} p(\vec{s}^j(0), \dots, \vec{s}^j(T-1) | I(0), \dots, I(n-1), \theta(0), \dots, \theta(T-1))$$



! Robust solution for 3D+t problems

Incremental Estimation of Patient-Specific Parameters from Cardiac Images

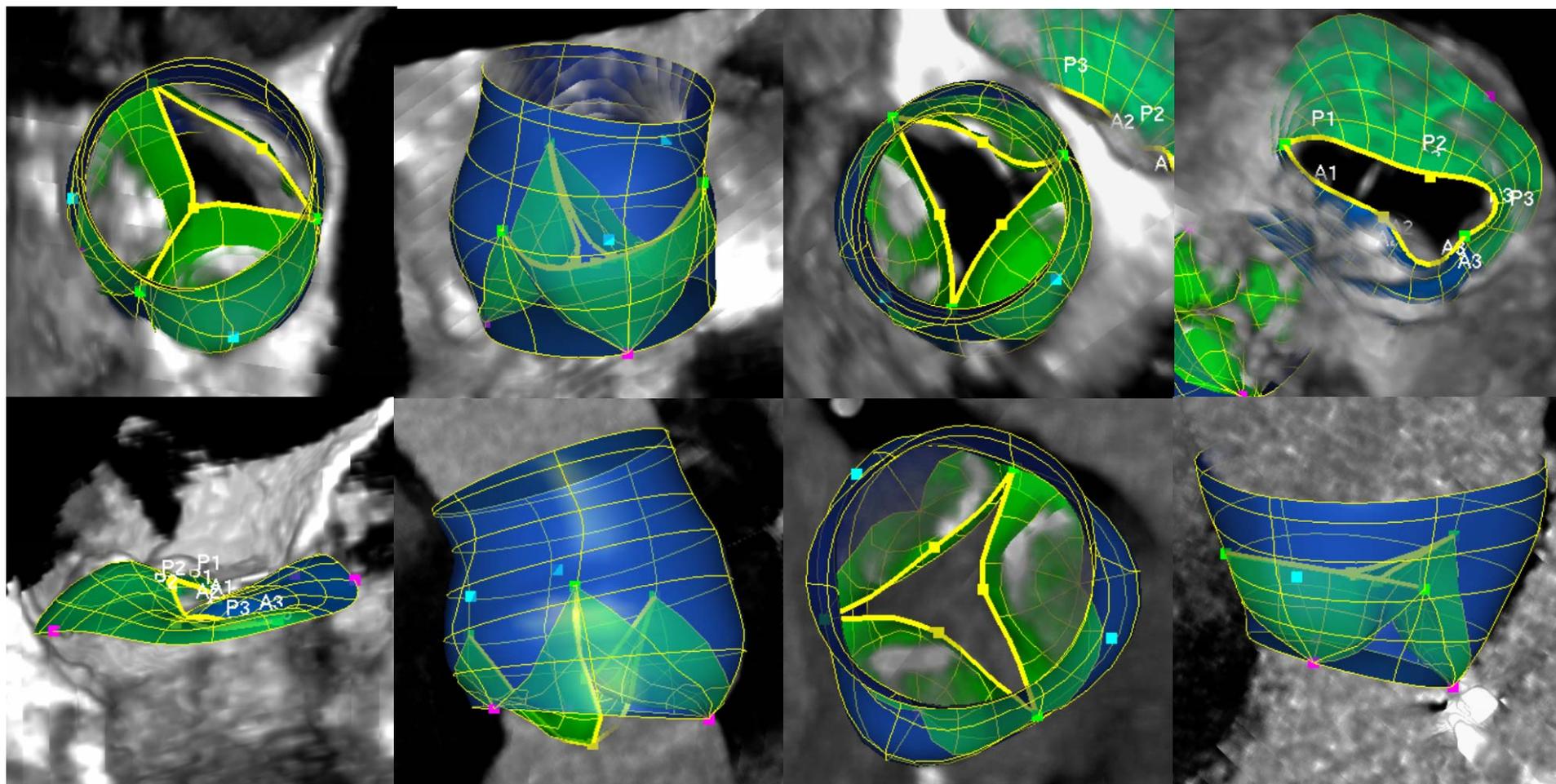
SIEMENS



Ionasec et al. TMI2010, Zheng et al. TMI2008, Ionasec et al. ICCV2009, Yang et al. ICCV2008

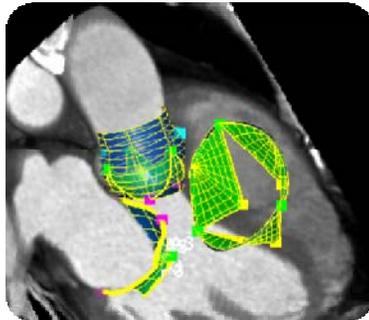
Patient-Specific Modeling of the Aortic and Mitral Valve from TEE and CT - Pathologies

SIEMENS

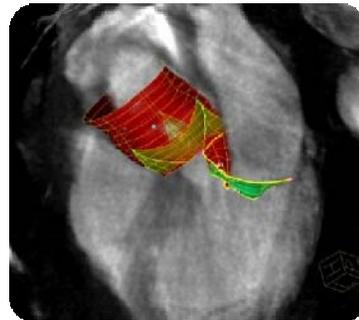


Patient-Specific Modeling of the Heart Valves from Multi-modal Images: Diagnosis and Planning

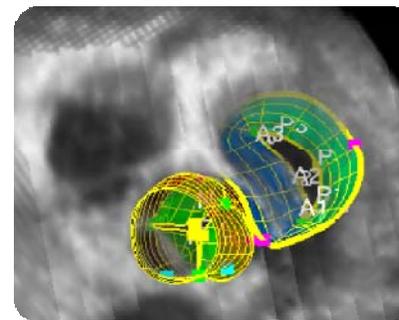
SIEMENS



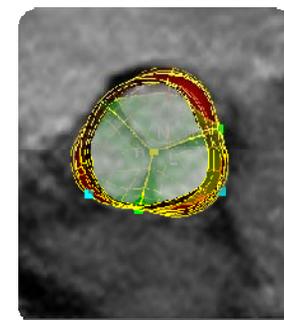
CT (Syngo.via VA11)



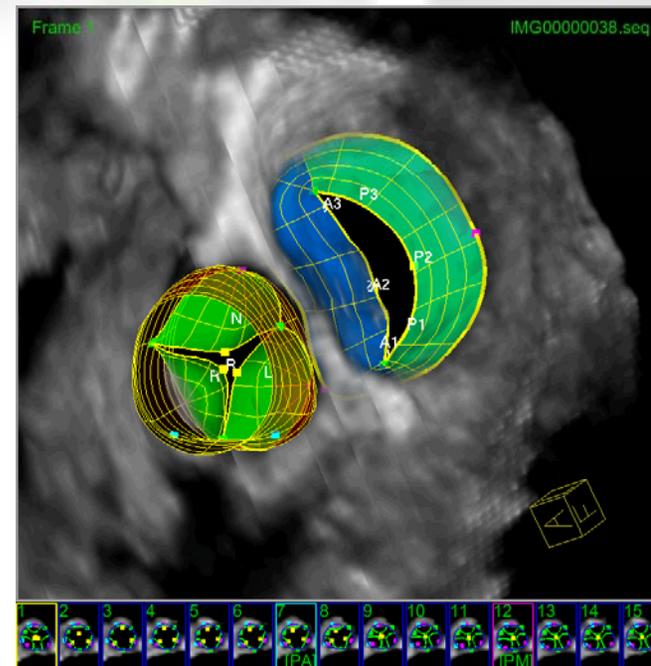
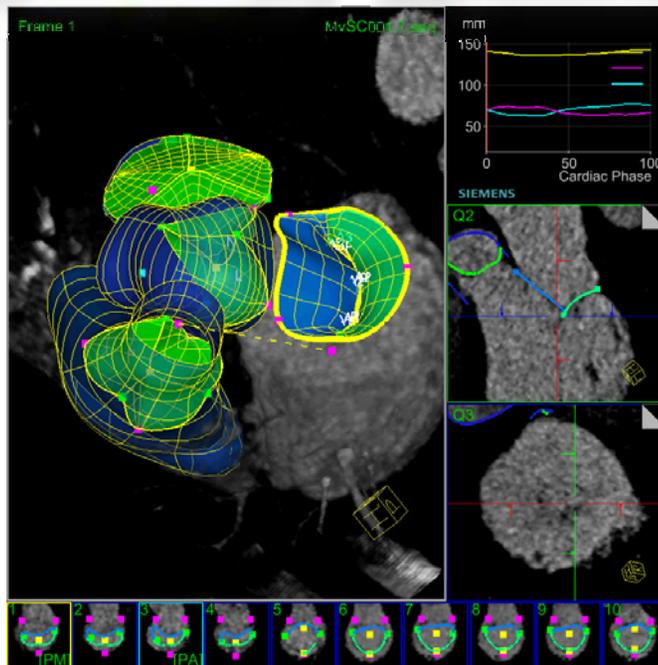
DynaCT



US (SC2000)

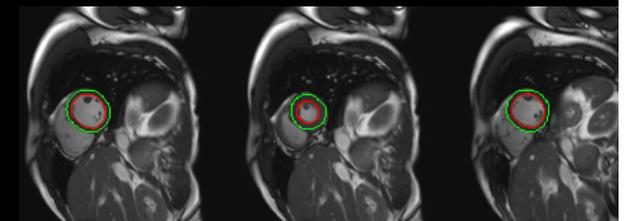
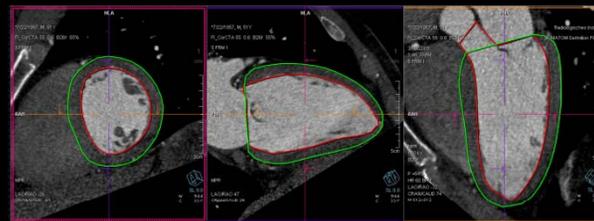
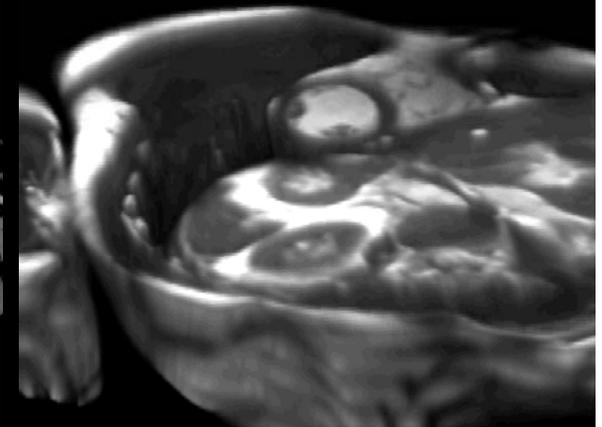
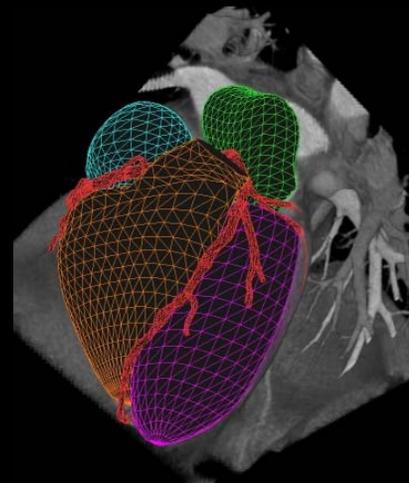
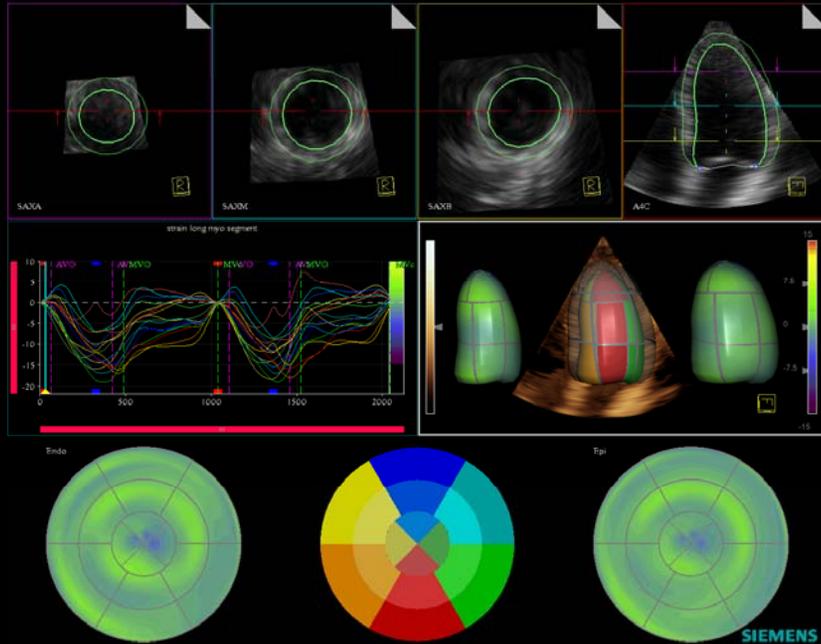


MRI



2011 MICCAI Young Scientist Award

A Unified Heart Model to Analyze Anatomy and Dynamics from Multi-modal Cardiac Data



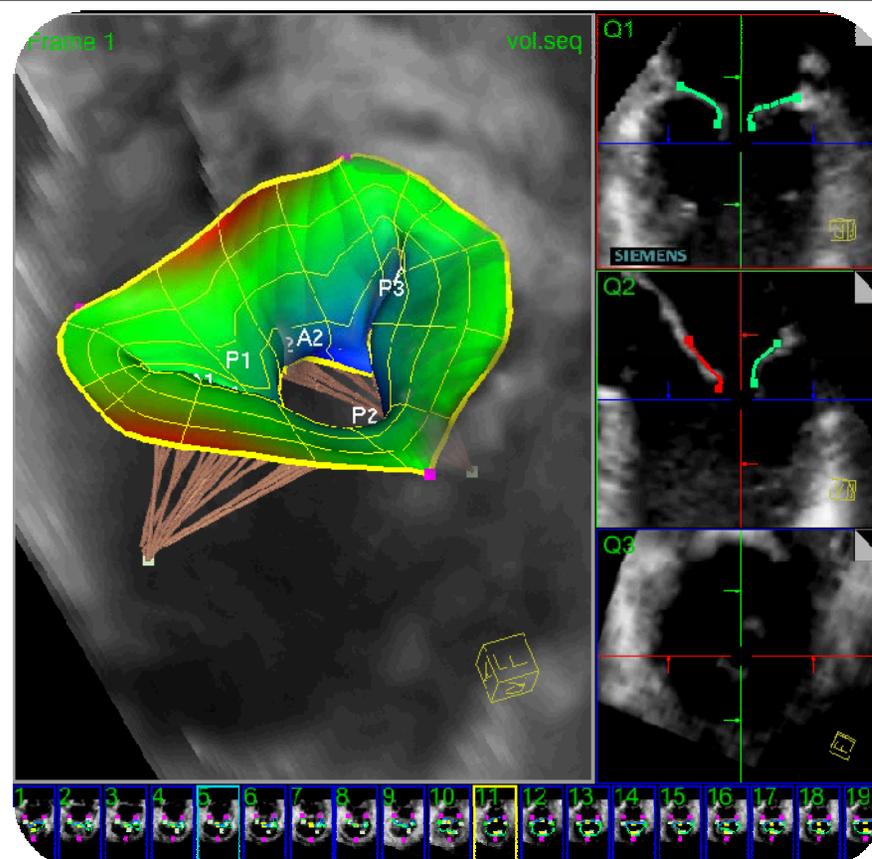
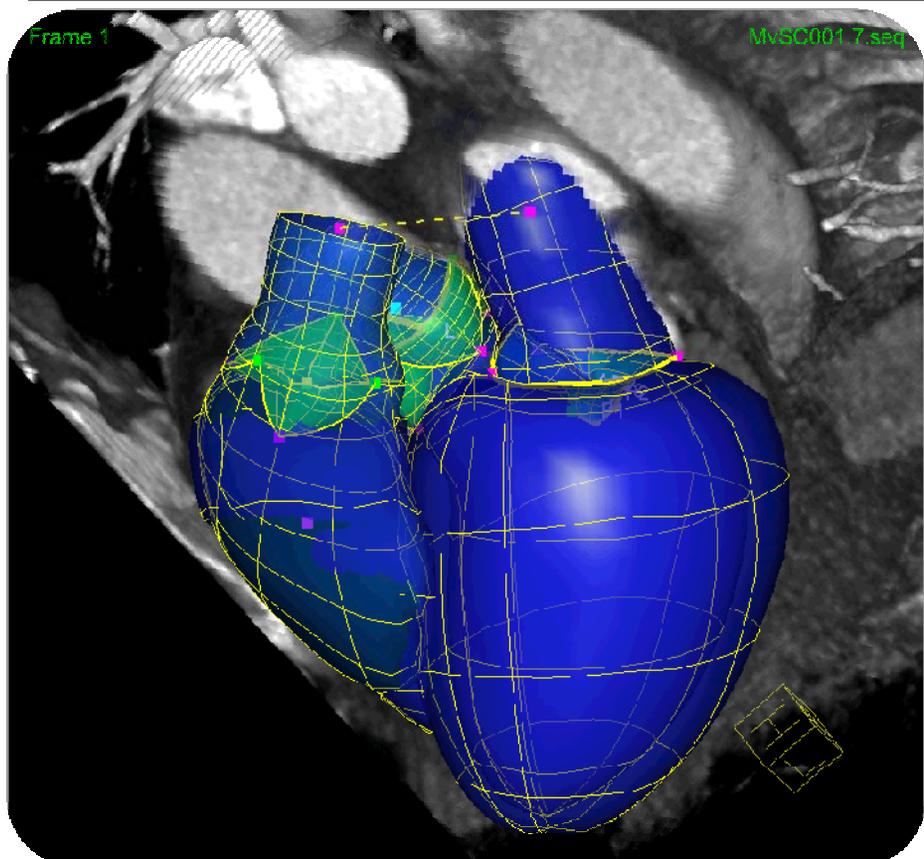
4D Echocardiography

Cardiac CT

Cardiac MRI

Patient-Specific Modeling of the Heart Valves from Multi-modal Images: Diagnosis and Planning

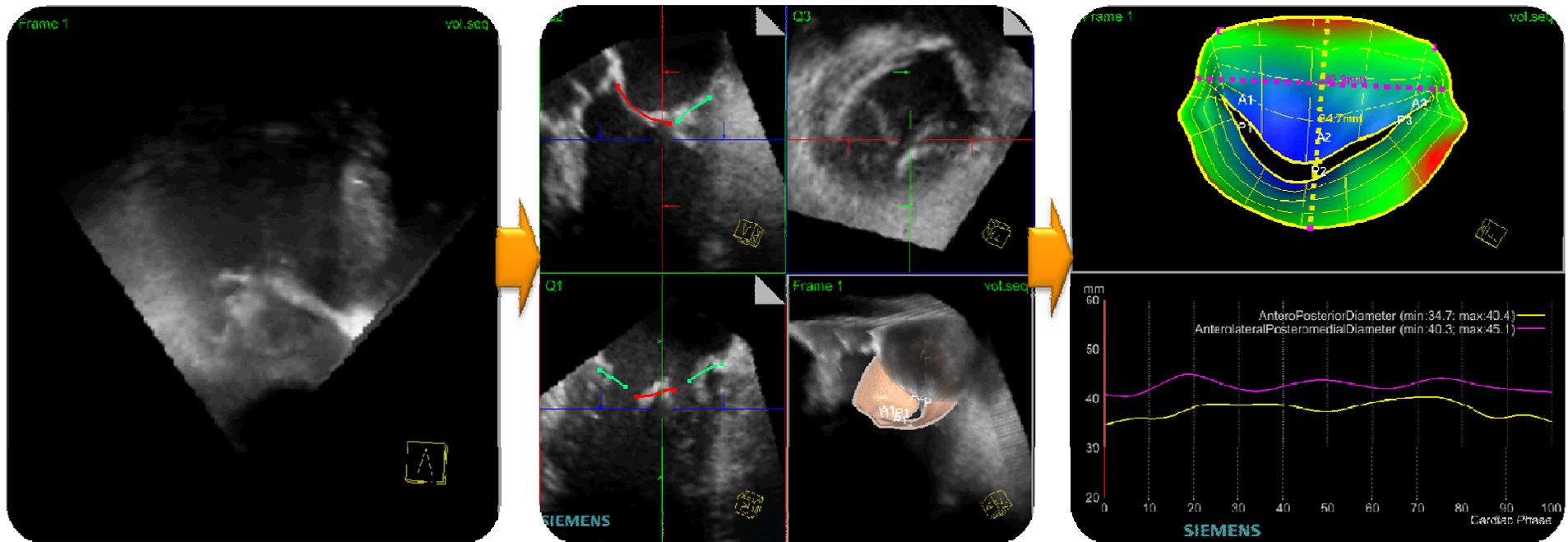
SIEMENS



- 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

SIEMENS

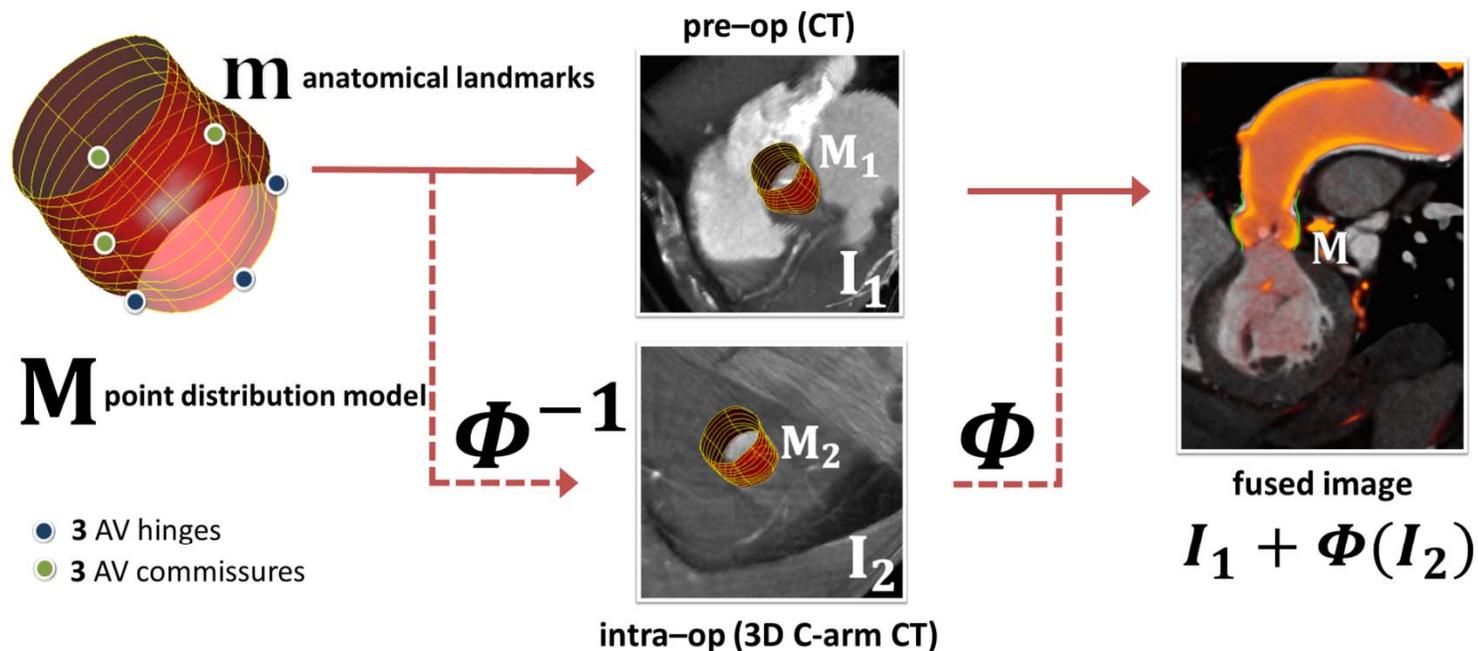


Modeling and Analysis of Anatomy and Dynamics of the Heart Valves

- 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

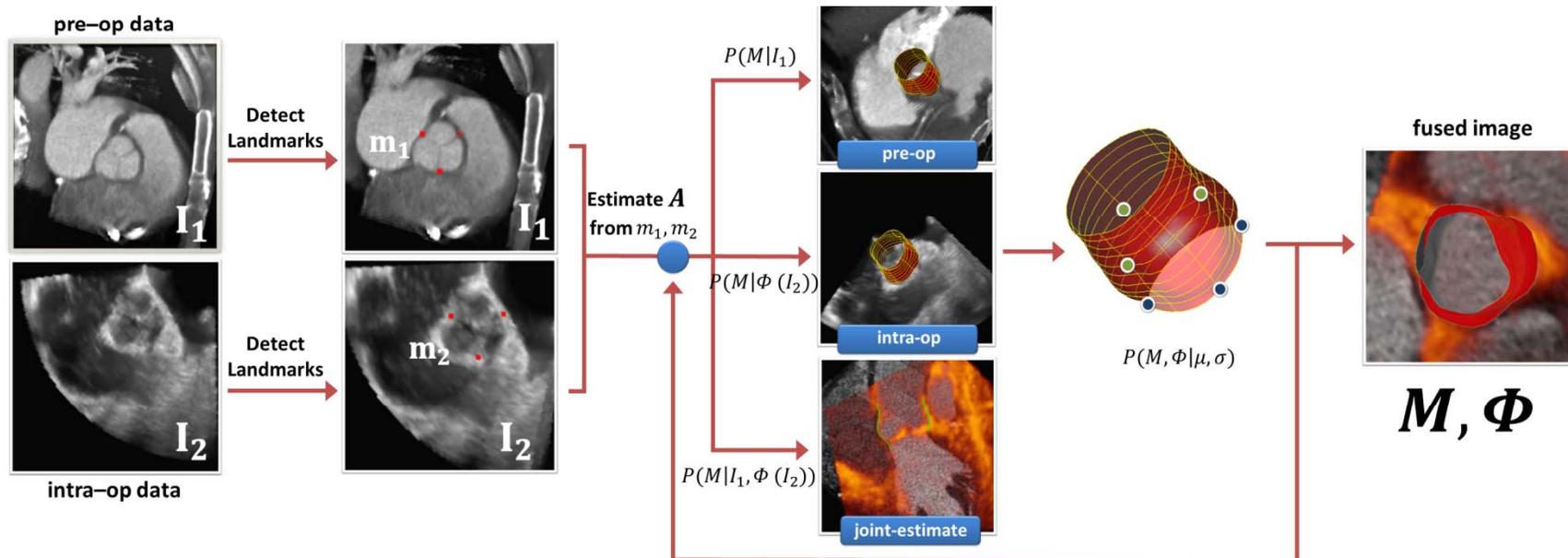
Fusion of Pre-operative and Intra-operative Data



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

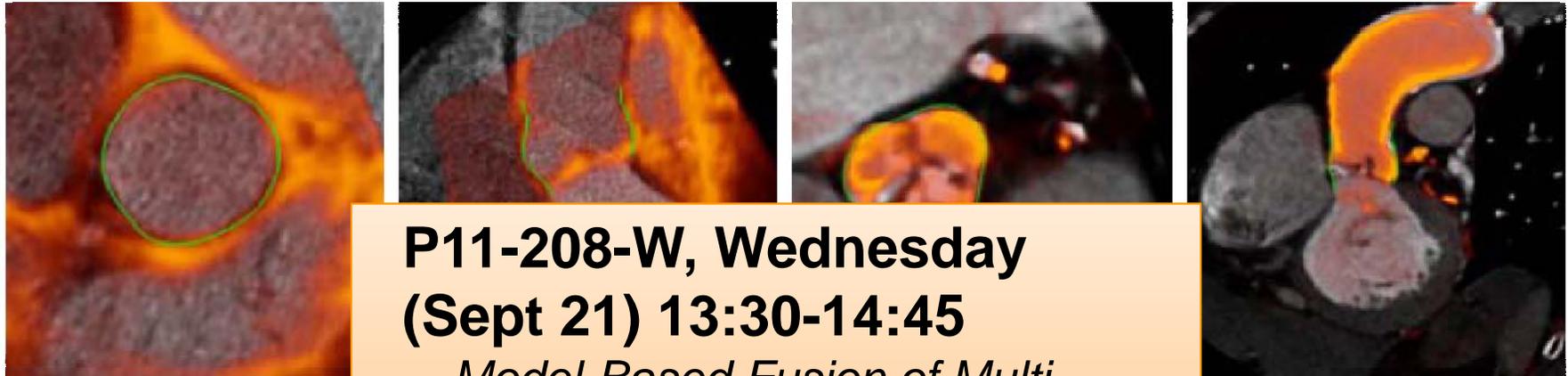
Fusion of Pre-operative and Intra-operative Data

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



- **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



**P11-208-W, Wednesday
(Sept 21) 13:30-14:45**

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

	Mean	STD	Median	Mean	STD	Median	Fusion approach
CT-TEE [mm]	1.22	0.23	1.13	1.09	0.22	1.10	
CT-3D C-arm CT [mm]	1.96	0.54	1.99	1.73	0.49	1.79	

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

Physically-Constrained Modeling

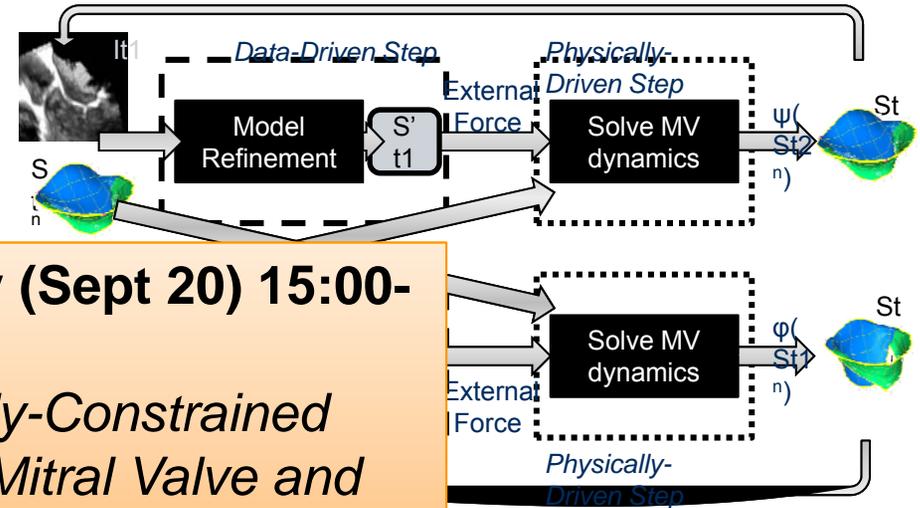
Physically-Driven Step

Transformations Ψ and ϕ estimated by solving dynamics equation (isotropic linear elastic⁵, co-rotational finite element⁶):

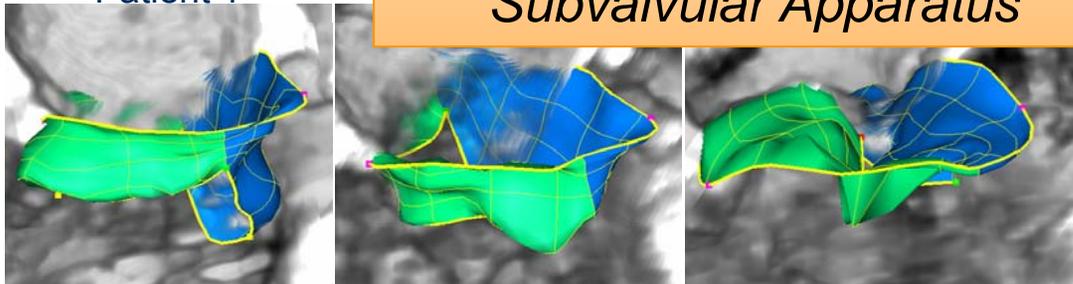
$$M\ddot{U} + C\dot{U} + KU = F_{ext}(\mathbf{v}_{t_2}^n) = -k(\mathbf{v}_{t_2}^n - \mathbf{v}_{t_2}^n)$$

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

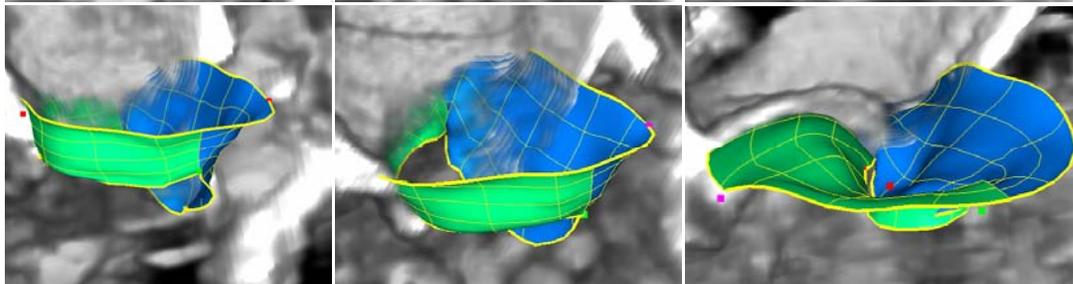
Robust Physically-Constrained Modeling of the Mitral Valve and Subvalvular Apparatus



Unconstrained Estimation



Constrained Estimation

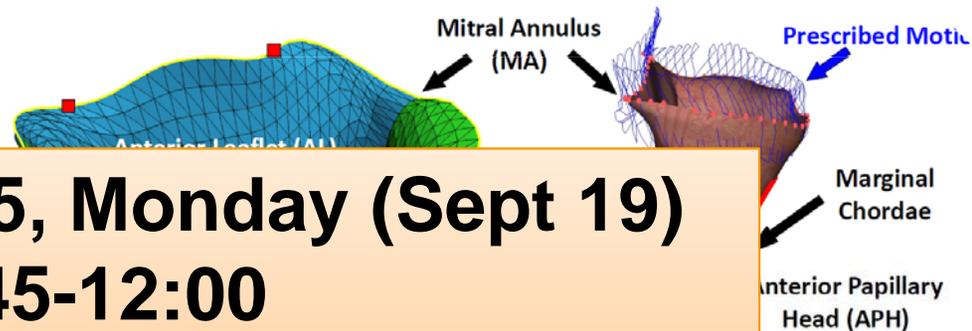
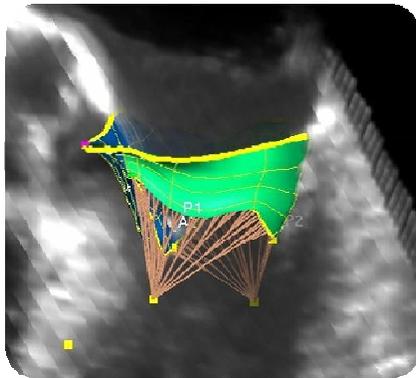


$$\begin{cases} S_{t_1} = \arg \max_{\hat{S} \in \Omega} p(\hat{S} | I_{t_1}) \\ S_{t_2} = \arg \max_{\hat{S} \in \Omega} p(\hat{S} | I_{t_2}) \\ S_{t_2} = \phi(S_{t_1}) \text{ and } S_{t_1} = \psi(S_{t_2}) \end{cases}$$

Comprehensive Therapy Modeling and Simulation

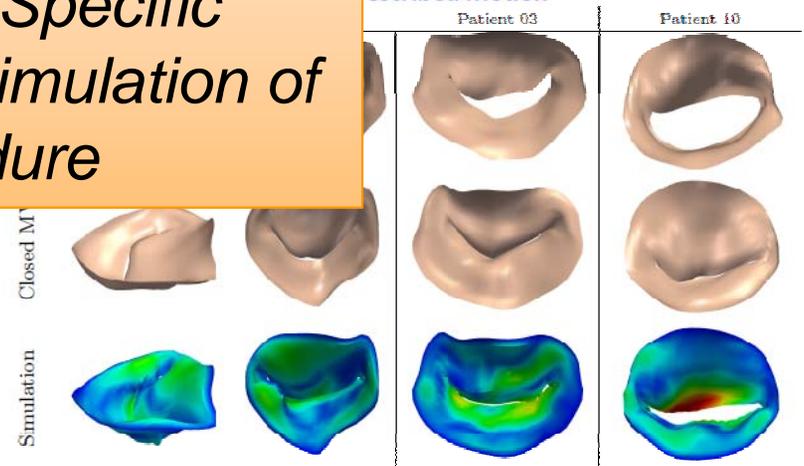
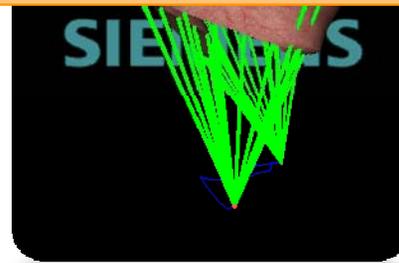
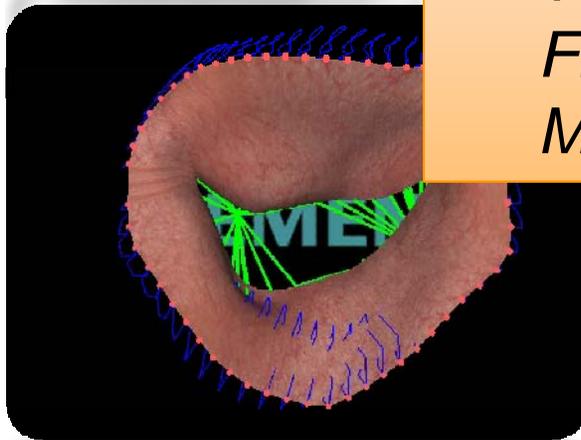
1) Automatic model detection

2) Automatic model generation for simulations



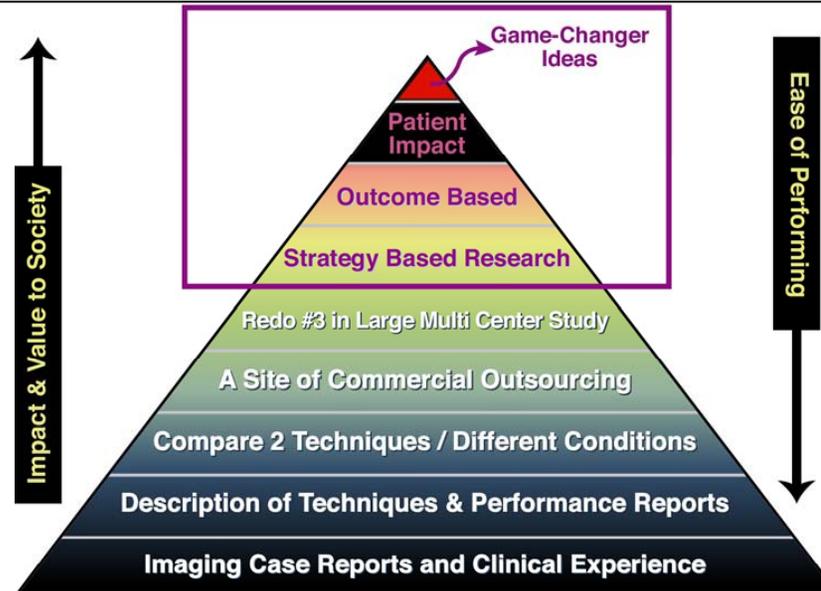
**O1-5, Monday (Sept 19)
10:45-12:00**

*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

Summary



- 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 ?