Robust Model-based 3D/3D Fusion using Sparse Matching for Minimally Invasive Surgery

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Motivation

Valvular Heart Disease

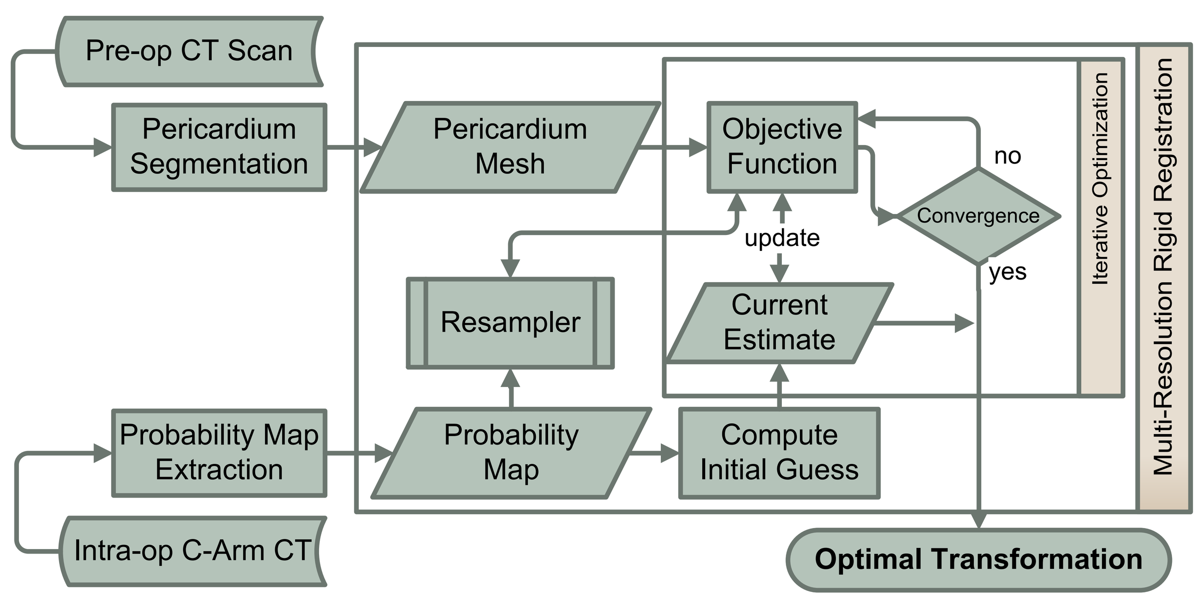
➔ Significant morbidity and mortality rates

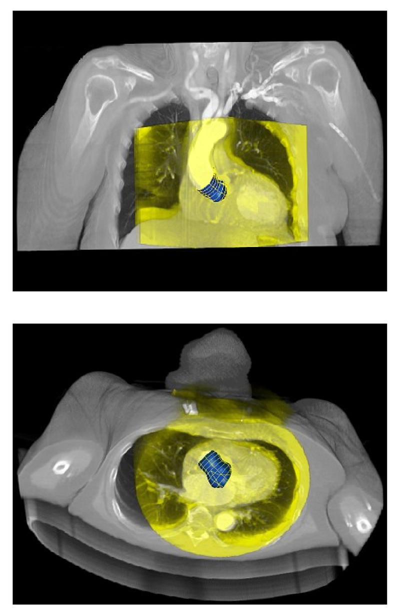
Minimally Invasive Surgery

- Treatment of patients previously declared inoperable [1]
- No direct access to the heart
  - ➔ Image navigation and guidance is essential
- Intra-operative data quality is low

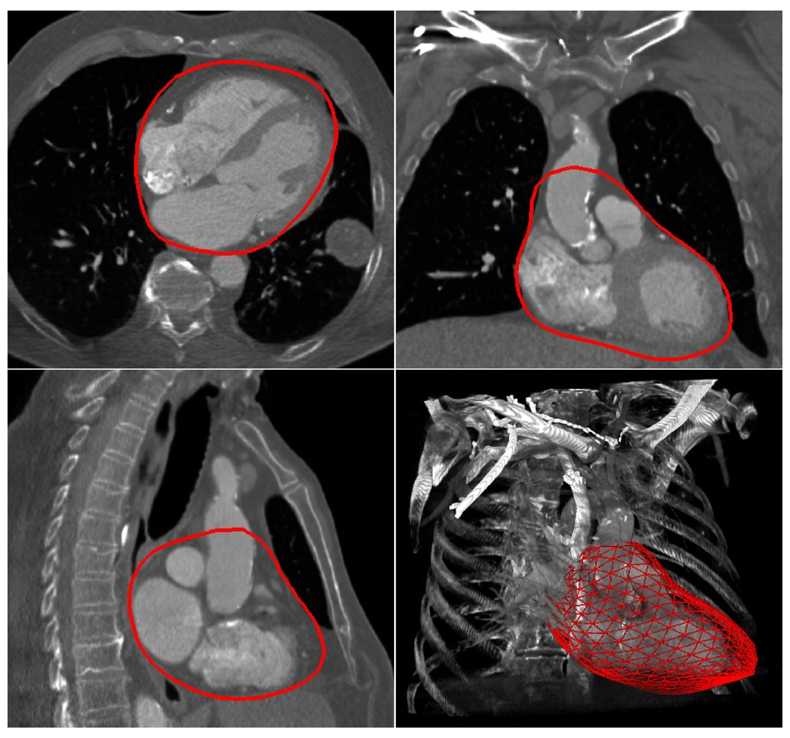
➔ **Fuse available high-quality pre-operative data to display valuable diagnostic information during surgery**

Fusion Workflow





Pre-operative Image | Image Processing | Intra-operative Image



Pericardium segmentation [2]

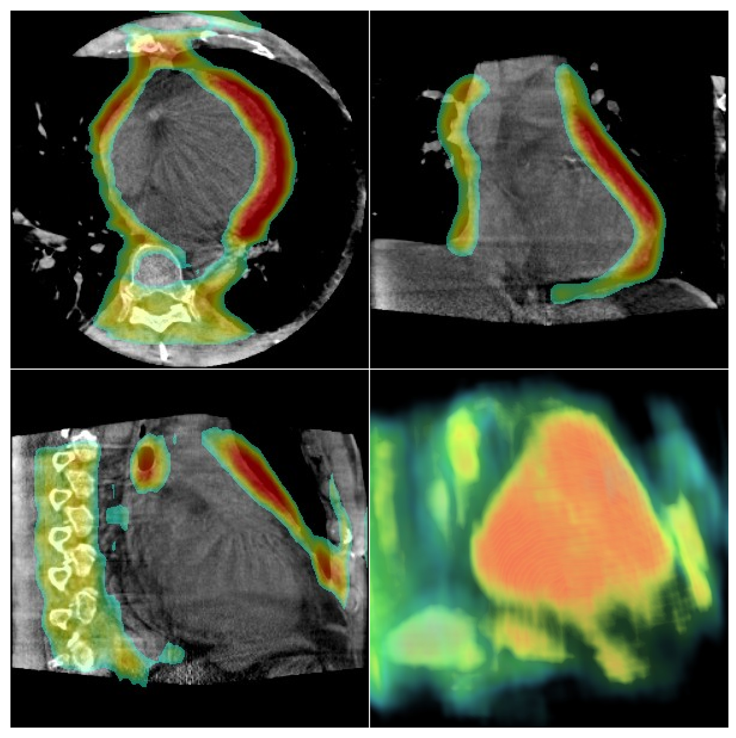
- Marginal Space Learning
  - Estimate pose/scale
  - Align mean shape
  - Refine parameters using Statistical Shape Models
  - Post-processing

➔ Extensively evaluated on 288 patients

Probability map extraction

- Posterior of voxel belonging to pericardium contour
- Probabilistic Boosting Tree (PBT) [3]
  - Evaluate on each voxel
  - Trained on 393 images

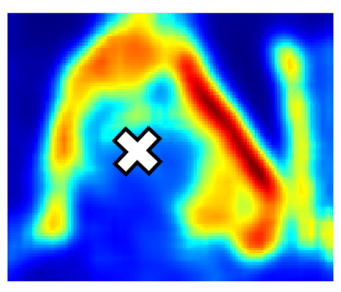
➔ Similar for images acquired with different acquisition protocols / contrast agents



Initialization and Optimization

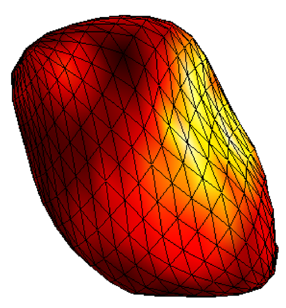
Initialization

- Estimate pericardium center in C-arm CT
  - ➔ PBT trained on probability maps
- Align with center of mesh model from CT



Prior Weights

- Reliability of probability map varies with region in image, independent of the patient
- Penalize points that are likely to be contained in low-confidence regions



Multi-resolution BFGS Optimization

Objective Function

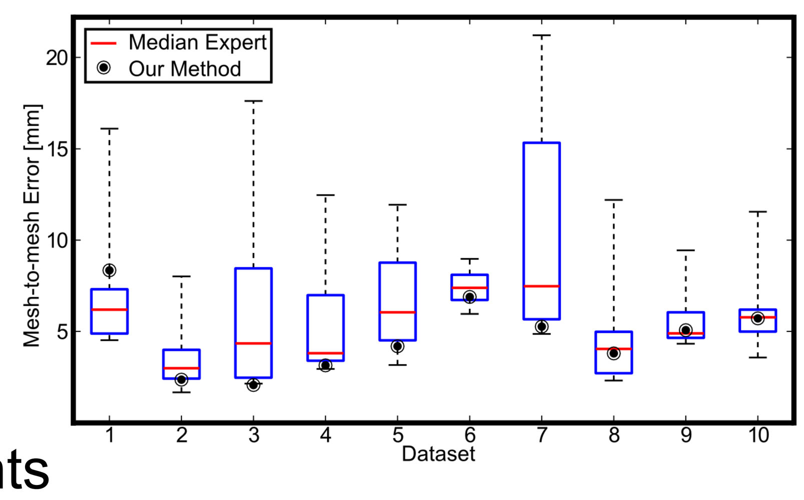
$$f(\boldsymbol{\theta} \mid \mathcal{A}, \tilde{\mathcal{F}}) = \frac{\sum_{\boldsymbol{p}\in\mathcal{A}} \text{is\_inside}(\boldsymbol{\theta}(\boldsymbol{p}), \tilde{\mathcal{F}}) \cdot \psi(\boldsymbol{\theta}(\boldsymbol{p}), \tilde{\mathcal{F}})}{\sum_{\boldsymbol{p}\in\mathcal{A}} \text{is\_inside}(\boldsymbol{\theta}(\boldsymbol{p}), \tilde{\mathcal{F}})}$$

- Rigid transformation parameters
- Probability map (*intra-operative C-arm CT*)
- Determine voxel in $\tilde{\mathcal{F}}$ that corresponds to transformed point $\boldsymbol{p}$ and return value inversely proportional to probability
- Segmented pericardium (*pre-operative CT*)
- Point inside boundaries of volume ? 1 : 0

Evaluation

Inter-user variability study

- 10 experts, 10 datasets
- 2-5 minutes per expert per dataset



Quantitative Evaluation

- Mesh-to-mesh error
- With / Without prior weights
- Comparison to state-of-the-art image-to-image fusion

Method	Without Prior Weights		With Prior Weights		State-of-the-Art		With Prior Weights	
Anatomy	*Pericardium*	*Aortic Valve*	*Pericardium*	*Aortic Valve*	*Pericardium*	*Aortic Valve*	*Pericardium*	*Aortic Valve*
# Data	88	43	88	43	47	21	47	21
Mean	**7.57 mm**	7.17 mm	**5.60 mm**	4.63 mm	**7.19 mm**	6.33 mm	**5.03 mm**	4.45 mm
Std	4.38 mm	7.10 mm	1.81 mm	1.90 mm	4.86 mm	4.71 mm	1.80 mm	2.14 mm
Median	6.91 mm	5.52 mm	5.29 mm	4.64 mm	4.96 mm	4.56 mm	5.02 mm	4.32 mm

Conclusion

Our registration approach is

- **Robust**: quantitative evaluation, inter-user variability study
- **Accurate**: 5.6 mm / 4.6 mm error for anchor / target anatomy
- **Fast**: 2.93 sec on consumer laptop
- **Application-specific**: Navigation in cardiac procedures

References

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