4D Statistical Shape Model of the Heart for X-Ray Projection Imaging

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Context

- C-arm CT dominant in interventional angiography
  - Acquisition times of $\approx 10$ s
- Motion compensation:
  - 4D reconstruction
  - Improved guidance
- Performance evaluation
  - Exhaustive testing
  - Normal and pathologic cases
- X-rays: somewhat "unhealthy"
  - No ground-truth for real data

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- Need for artificial data
  → Simulation frameworks
  → Numerical phantoms

- Enable comparison:
  → Framework: CONRAD

- XCAT\(^1\)
  → 3D from Visible Human
  → Motion from one male patient
  → Developed for ET
  → Licensing fee (small)

\(^1\) Segars et al., “4D XCAT phantom for multimodality imaging research”. April, 17. 2015 | Unberath | FAU Erlangen-Nürnberg, Stanford University | 4D Statistical Human Heart Phantom
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Goals

A new phantom should be:

• available
• dynamic (temporal variation)
• versatile (inter-subject variation)
• clinically relevant

Dynamic statistical shape model of the heart.
Contents

Training set generation
  Registration Pipeline
  Results and conclusions

Model-building and simulation
  Alignment and principal component analysis
  Results and conclusions
Problem statement

Learn valid behavior from training set

*Many shapes from diverse anatomies.*

Point correspondence **must** be established/preserved.

?- Data-driven segmentation (incl. manual)

! Registration-based segmentation

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*How "many" and how "diverse"?*
General idea

Propagate landmarks from atlas to new images.\textsuperscript{3,4}

What is needed?

- Landmarked atlas segmentation
- Registration pipeline

What atlas? What pipeline?

\textsuperscript{3} Frangi et al., “Automatic construction of multiple-object three-dimensional statistical shape models: Application to cardiac modeling”.

\textsuperscript{4} Ordas et al., “A statistical shape model of the heart and its application to model-based segmentation”.

Atlas segmentation

1. Manual segmentation in ITK Snap
2. Mesh generation (coarsening and smoothing)

Data set used:

- 45 y/o female, 78% phase
- $512 \times 512 \times 241$ pixels
- $0.29 \times 0.29 \times 0.5$ mm spacing
Atlas segmentation

Figure: Axial slice

Figure: Surface rendering
Registration

B-Spline-based registration pipeline:

Rigid:

- Similarity transform
- Mutual information

Non-rigid: multi-resolution

- B-spline transforms
- Mutual information
Mutual information

Reduce uncertainty in X by knowing Y
No explicit form of dependency needed

\[
\int \int p_{fm}(f(x), m(y)) \log \left( \frac{p_{fm}(f(x), m(y))}{p_f(f(x)) p_m(m(y))} \right) \, dx \, dy
\]

\(f, m\) are the fixed and moving image
\(p_f\) and \(p_m\), and \(p_{fm}\) are the marginal and joint histograms
B-Spline transforms

Smooth transforms defined on control grid

*Weighted sum of points in finite support region*

**1D B-Spline**

\[ T(x) = \sum_{n=0}^{d} B_n(u) \Phi_{k+n}, \]

\[ u = \frac{x}{n_x} - \left\lfloor \frac{x}{n_x} \right\rfloor \in [0, 1] \]

\[ k = \left\lfloor \frac{x}{n_x} \right\rfloor - 1 \]

\( B_n(u) \): B-Spline basis function (≡ weights)

\( \Phi_i \): control points in grid
Evaluation

Procedure

• Fix registration parameters
• Register to data at all cardiac phases

Quality assessment

Representative female and male patient data

• Visual evaluation
• Expert ranking
Visual evaluation

Female, End-Diastole: Coronal view

Male, End-Systole: Coronal view
Expert ranking: Results & Discussion

Average scores throughout the cardiac cycle

- 3 experts: Grades ∈ [0, 5], 5 ≡ best
- Overall score: $3.33 \pm 0.51$
- Atlas segmentation is at 78% phase (end-diastole) → Induces bias.
Conclusions

- Reduce bias: create atlas from "mean heart"
- Automatic registration: parameters fixed
  → Automatic parameter tuning at run-time?

Training set generation is not time-sensitive but crucial.
→ Refinement of the automatic segmentation (e.g. local adaptation).
Best case scenario

Atlas segmentation:  
Axial view

Female, End-Diastole:  
Axial view
Procedure

Statistical shape model generation

Four step process:

1. Obtain training shapes
2. Establish point correspondence
3. Align shapes
4. Extract principal modes of variation
Training set

20 ten phase CTA data sets

9 male patients: 23-92 y/o (59.56 ± 25.10 years)
11 female patients: 51-81 y/o (70.45 ± 12.89 years)

Ejection fractions: 52.13 ± 9.11%
Alignment

Generalized Procrustes Analysis

*Pose (and scale) is not part of shape.*

1. Center and scale input samples $X_i$
2. Rotate all $n$ shapes $X_i$ to fit $X_1$
3. Calculate consensus shape $Y$
4. Until convergence:
   - Rotate and scale $X_i$ to consensus $Y$
   - Reassure proper scaling
   - Calculate residual change
PCA

Goals of Principal Component Analysis

- Extract most important information from the data
- Reduce dimensionality of the data
- Simplify description of shapes
PCA: Procedure

Procedure

1. Compute mean shape \( \bar{X} \)
2. Covariance matrix: \( S = \sum_{i=1}^{n} (X_i - \bar{X})(X_i - \bar{X})^T \)
3. Solve: \( S \Phi_k = \lambda_k \Phi_k \)
4. Pick largest \( c \) principal components \( \Phi_k \)
e.g. cumulative variance \( r > 75, \ldots, 99\% \)

Statistical shape model: \( \{ \bar{X}, \Phi \} \)
PCA: Procedure cont.

Statistical shape model: \( \{ \bar{X}, \Phi \} \)

Shape description

\[
X_i \approx \bar{X} + \sum_{k=1}^{c} \beta_{i,k} \Phi_k
\]

\( \Phi_k: c < n \) principal modes of variation
\( \beta_k: \) principal components
PCA: Procedure cont.

Inter-subject and temporal variation.  
*Valid dynamic shapes from multi-phase data.*

1. Shape models at phase $p$: $\{\bar{X}, \Phi\}^{(p)}$
2. Principal components of shapes: $\beta_i^{(p)}$
3. Build component vector:  
$$\beta_i = (\beta_i^{(1)}, \cdots, \beta_i^{(p)})$$
PCA: Procedure cont.

PCA on component vectors: \( \{ \bar{\beta}, \rho \} \)

Compact interface for dynamic model generation

**Dynamic model**

\[
(\kappa^{(1)}, \ldots, \kappa^{(p)}) = (\bar{X}^{(1)}, \ldots, \bar{X}^{(p)}) + (\Phi^{(1)}, \ldots, \Phi^{(p)})(\bar{\beta} + \rho \delta)
\]

Interpolation for continuous representation.
Results: Generalization

Cross validation: leave-one-out test

*Capability to represent unseen instances.*

- Exclude shape from model
- Fit model to shape
- Compute error

90% variation: \( 5.00 \pm 0.93 \) mm
95% variation: \( 4.89 \pm 0.90 \) mm
Results: Specificity

Random shape sampling

Validity of new instances.

- Generate random component vectors
- Compute distance to nearest training shape

Static: 1000 samples  $7.18 \pm 0.45 \, mm$
Dynamic: 100 samples  $7.30 \pm 0.97 \, mm$
Results: Variability at diastole

Decreasing variance $\mu$ from left to right: $\delta_b = -\mu_b/2$ top, $\delta_b = \mu_b/2$ bottom, and $\delta_b = 0$ mid.
Results: Projection imaging

Volume rendering

Projection image
Conclusions

- Large variation among few samples
- Deteriorates specificity
  → Revisit training set generation

- Currently: anatomy at rest determines contraction
  → Multi-linear PCA
  → Thorax model, Breathing motion, ...

To our knowledge the first open-source, dynamic statistical shape model of the heart.\(^5\)

\(^5\)Available at: conrad.stanford.edu