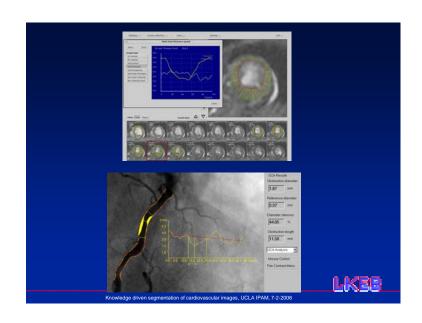
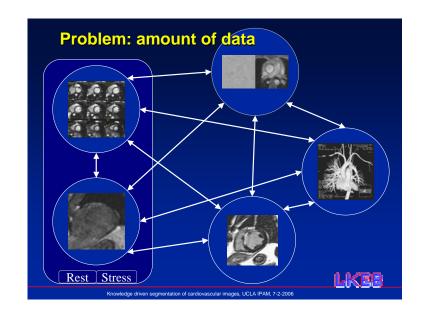


Introduction Introduction: why prior knowledge? Knowledge guided image processing Model driven Data driven High level reasoning Future directions





Goal: automated segmentation

- Less work!!
- More objective
 - · Less difference between observers
 - Less difference in repeated measurements
- More reproducible
 - Easier to compare with others
 - Easier to perform follow ups
 - Less patients in trial



Knowledge driven segmentation of cardiovascular images, UCLA IPAM, 7-2-2006

Why knowledge?

- Robust segmentation only possible using knowledge about:
 - Anatomical shape + shape variation + motion
 - Spatial context of organs
 - Intensity and data characteristics
 - Behavior of your algorithms
- Modality independent:
 - Current applications:
 - Cardiac MR
 - Cardiac CT
 - LV Angiography
 - Echocardiography



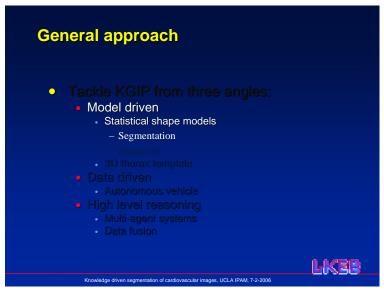
Introduction: why knowledge? LKEB

Knowledge driven segmentation of cardiovascular images, UCLA IPAM, 7-2-2006

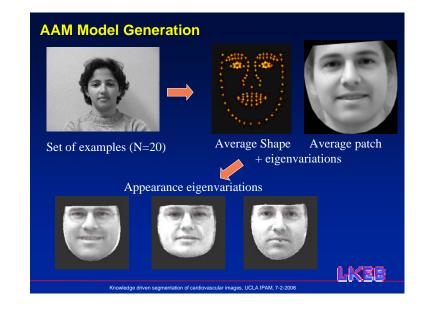
General approach

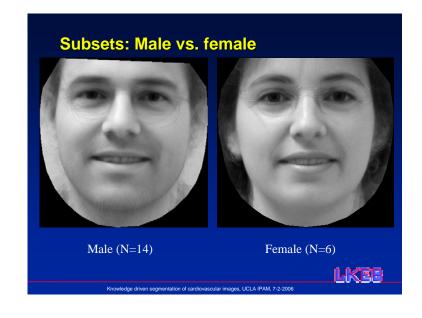
- Tackle KGIP from three angles:
 - Model driven
 - Statistical shape models
 - Segmentation
 - Diagnosis
 - 3D thorax template
 - Data driven
 - Autonomous vehicle
 - High level reasoning
 - Multi-agent systems
 - Data fusion













Active Appearance Models

- AAM's can be used for contour tracing by:
 - initially positioning the model
 - fitting the model to the underlying image along 'statistically plausible' deformations



Knowledge driven segmentation of cardiovascular images, UCLA IPAM, 7-2-2006



Matching AAM's

- To match an AAM to an image requires:
 - a criterion function e:
 - the RMS error of the 'difference image' between the model and the underlying image patch
 - a minimization procedure (Levenberg Marquardt / simplex)
 - derivatives of the criterion function with respect to all 'optimizable' parameters
 - can be estimated using multiple linear regression
 - examples of derivative images







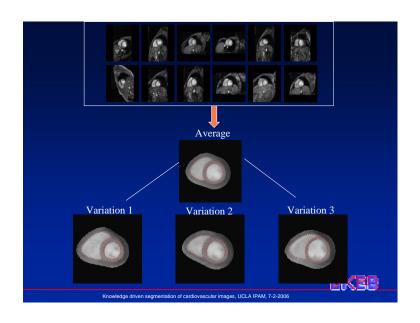


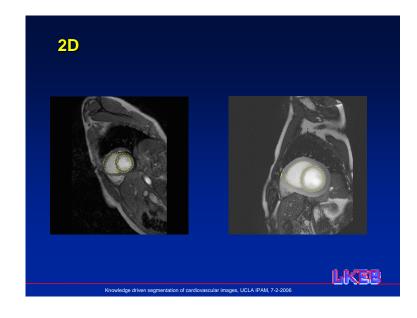


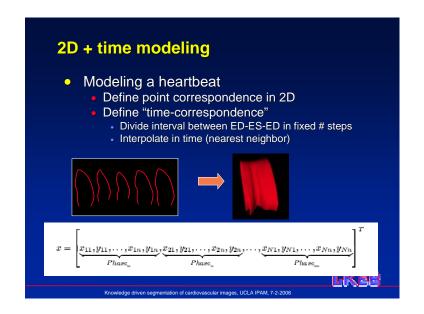


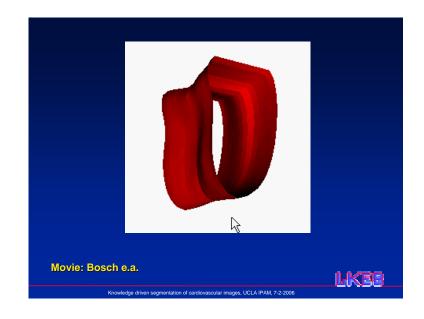


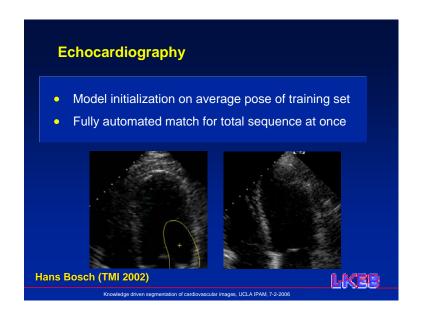


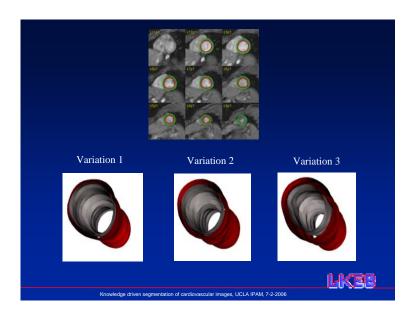


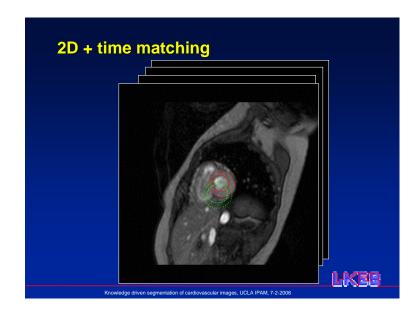


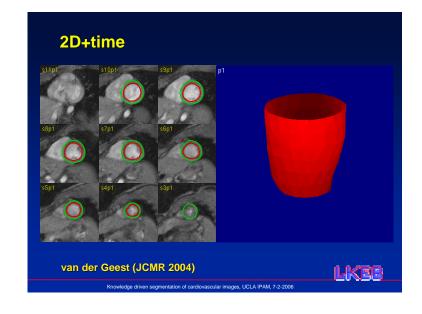


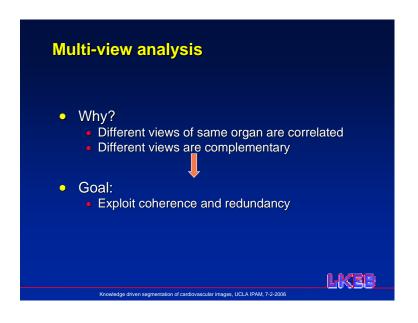


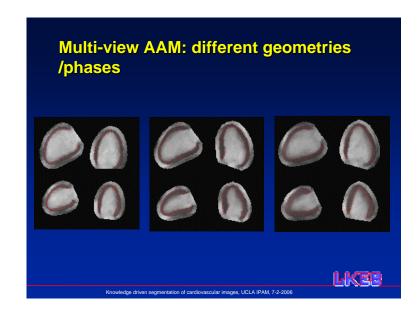


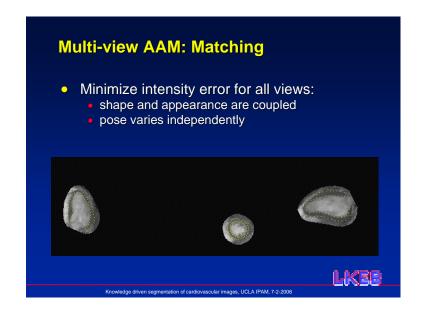


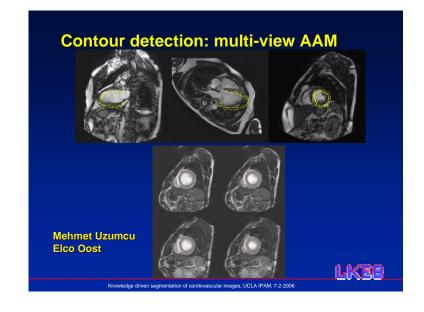


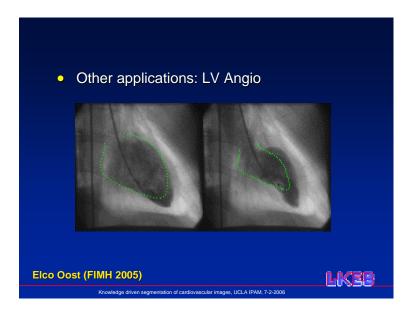


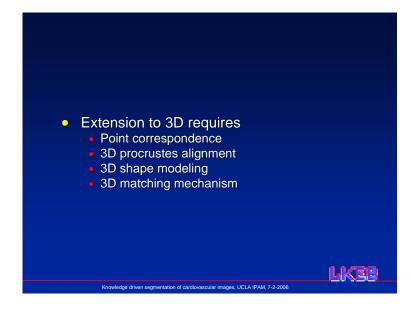












3D point correspondence

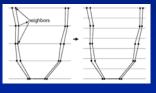
- Problem: no natural ordering in 3D
- Solutions:
 - Application specific manual (Mitchell, Stegman)
 - Through parameterization
 - Map to sphere
 - SPHARM (Brechbuhler)
 - MDL in 3D (Davies)
 - M-reps (Pizer group)
 - Object coordinate frame
 - Through registration
 - Deformable-mesh-to-binary-volume fitting (Kaus)
 - Non-rigid binary-binary registration (Frangi)



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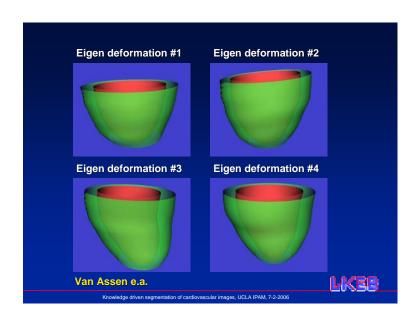
Application specific: manual

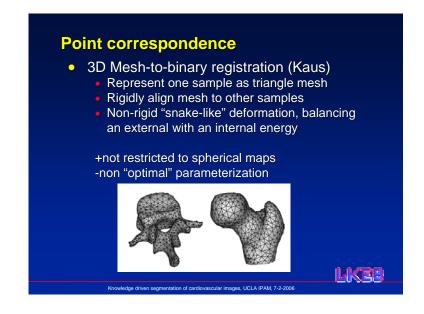
- Interpolate in through plane direction
- Fix orientation
- Radial sampling of each contour
- In cardiac MR case: problem: slice shift!

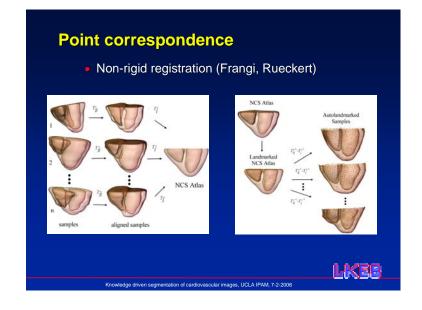


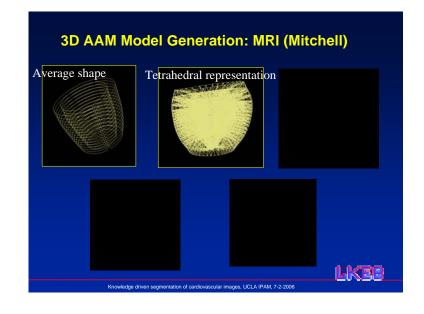


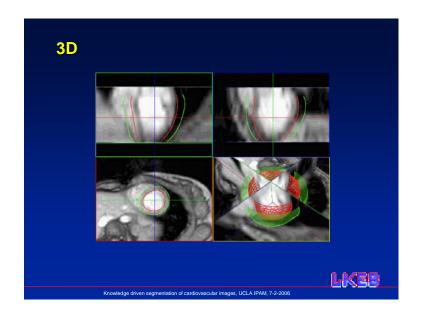




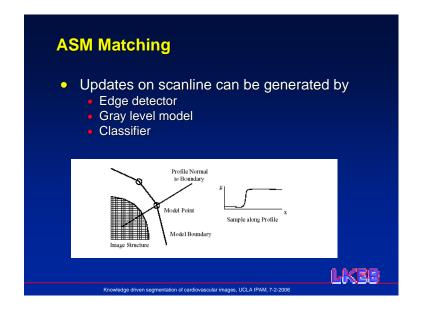






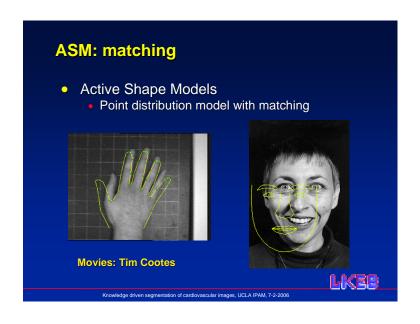


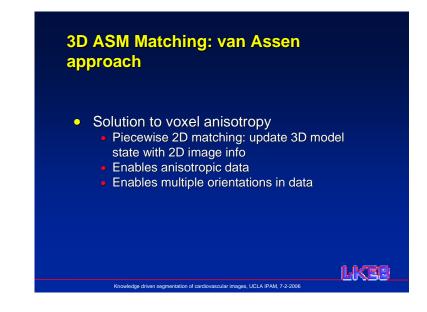


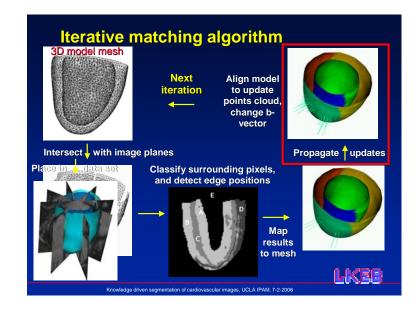


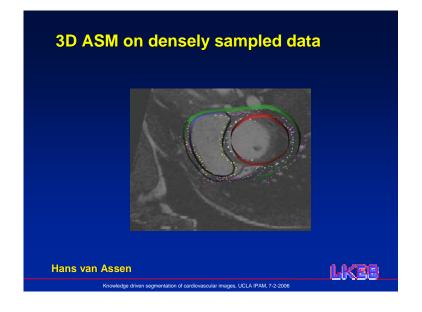
Vector y = candidate points Vector x = x̄ + Φb = current model state Align y to current shape in model frame

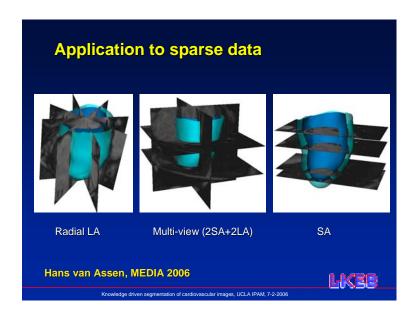
• Scale y with
$$1/(y \cdot \overline{x})$$
• Update model parameters to match y $b = \Phi^T(y - \overline{x})$
• Apply constraints on b
• Per parameter: $|b_i| \leq 3\sqrt{\lambda_i}$
• Mahalanobis distance: $\left(\sum_{i=1}^t \frac{b_i^2}{\lambda_i}\right) \leq M_i$
• Repeat until convergence

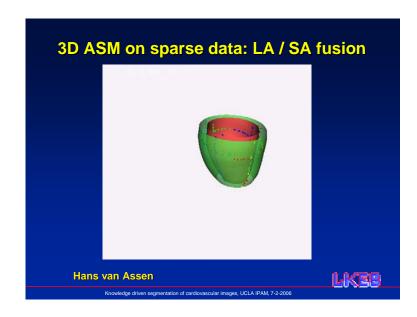












ASM versus AAM

- 3 key differences:
 - ASM only uses texture in small region around landmark, AAM complete patch
 - ASM searches around current positions, AAM only under current position
 - ASM minimizes distance to boundary, AAM intensity difference



ASM versus AAM (Cootes)

- General
 - ASM is faster
 - AAM possible with fewer landmarks
 - AAM has "interpretable" convergence criterion
 - automatic failure detection (Thodberg, Stegmann)



Statistical model limitations

- How to balance training set?
- How many samples necessary?
- Manual annotation of training samples
- Local refinement necessary
- Dimensionality vs nr training samples



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3D ASM matching: Kaus approach

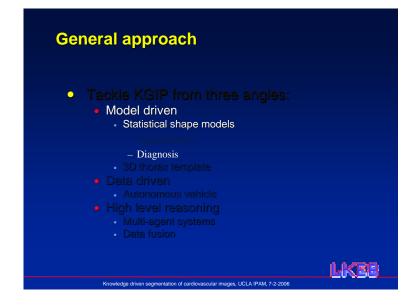
• Deformable model based on energy

$$E = E_{ext} + E_{int}$$

- Shape model is integrated in Eint
 - Term for PDM for each single surface
 - Term for connections between surfaces term
 - General shape & connectivity constraint term
- Local intensity model in E_{ext}
 - Every scanline has different feature detector (3 classes)







Computer-aided diagnosis Construct a model of normal motion Classify and localize deviations from normal Demo

LKEB

