Real-Time Active Shape Models for Segmentation of 3D Cardiac Ultrasound

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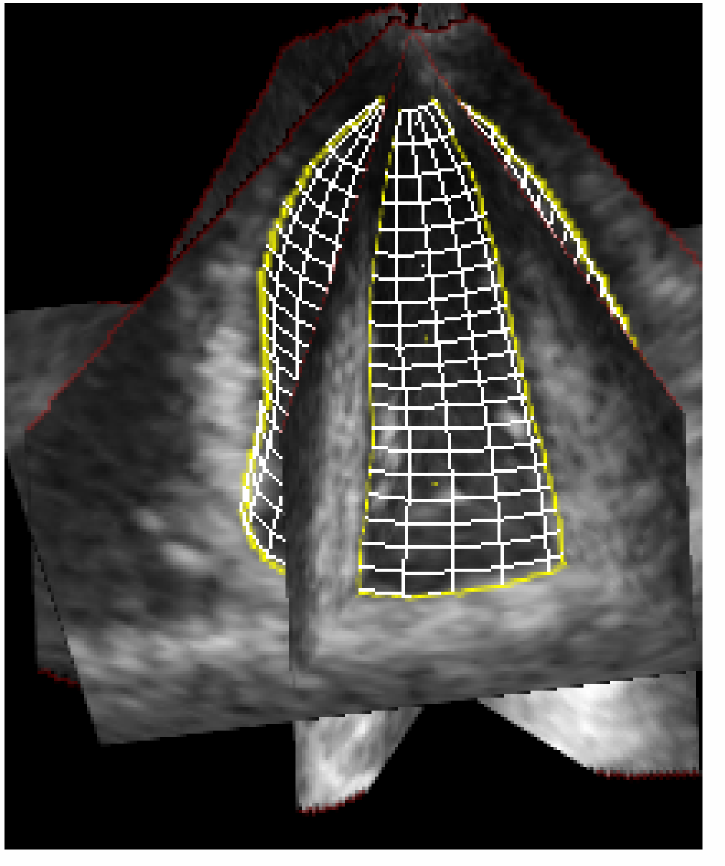
Background and aim

Background

- Rapid global function
- Intraoperative monitoring/ trending
- Lack of real-time 3D segmentation methods

Aim

- Real-time 3D segmentation of left ventricle.



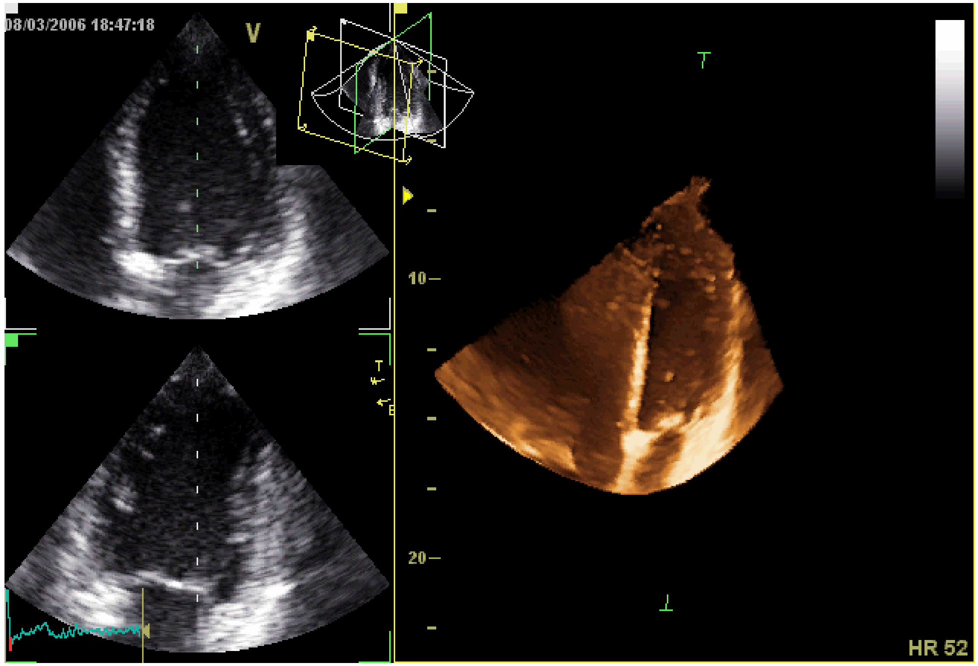
3D Ultrasound data

Characteristics

- Displayed in real-time
- 15-20 frames/sec
- ECG-gating over 4 heartbeats

Challenges:

- Shadows, drop-outs, noise, speckle, reverberations.



Previous work

Traditional deformable models

- Level sets, simplex mesh, FEM, statistical shape models
- May require hundreds of iterations
- Not suitable for real-time operation

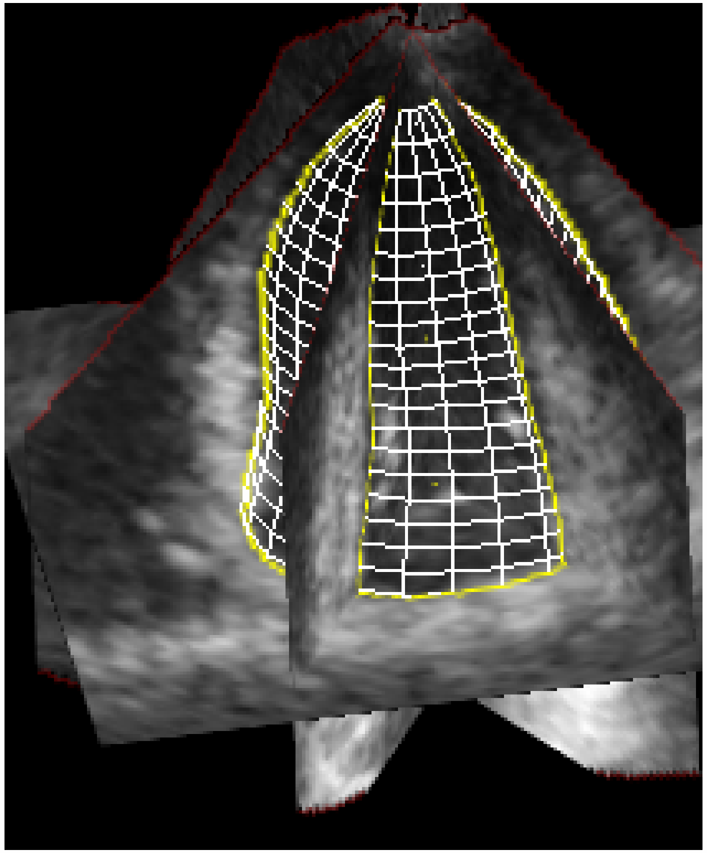
Kalman filter based methods

- Single iteration - Ideal for real-time operation
- Blake, Jacob, Comaniciu: 2D contours
- Orderud: 3D rigid ellipsoid model
  - Fast, not physiologically realistic.
- Orderud: 3D deformable spline model
  - Better regional accuracy, not limited to physiologically realistic shapes.

Kalman filter based segmentation

- Parametric deformable model, e.g. spline model, active shape model

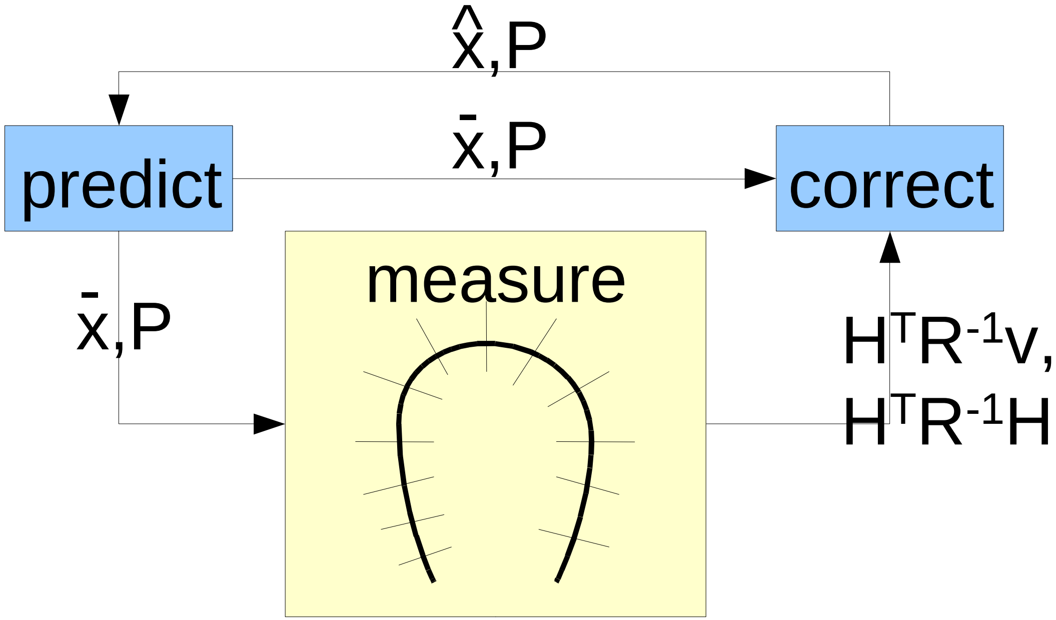
- Segmentation as ***estimation***
  - Sequential state estimation techniques to track the model parameters
  - Computational efficient algorithms, e.g. Kalman-filter



Processing overview

For each frame:

- *Predict* contour shape and position, using a kinematic model for each model parameter
- *Measure* edges in proximity of predicted surface
- Use measurements to *correct* prediction



Three-step process for each frame.

Glhfw#forvhg#irup#
vroxwlrq#lqvwhdg#ri#
lwhudwlyh#uhilqhphqw$

Deformable model (1/2)

3D active shape model (ASM)

Linear model consisting of:

- Average shape $\bar{\mathbf{q}}_i$
- Deformation modes $\mathbf{A}_i$

Built by PCA on training set

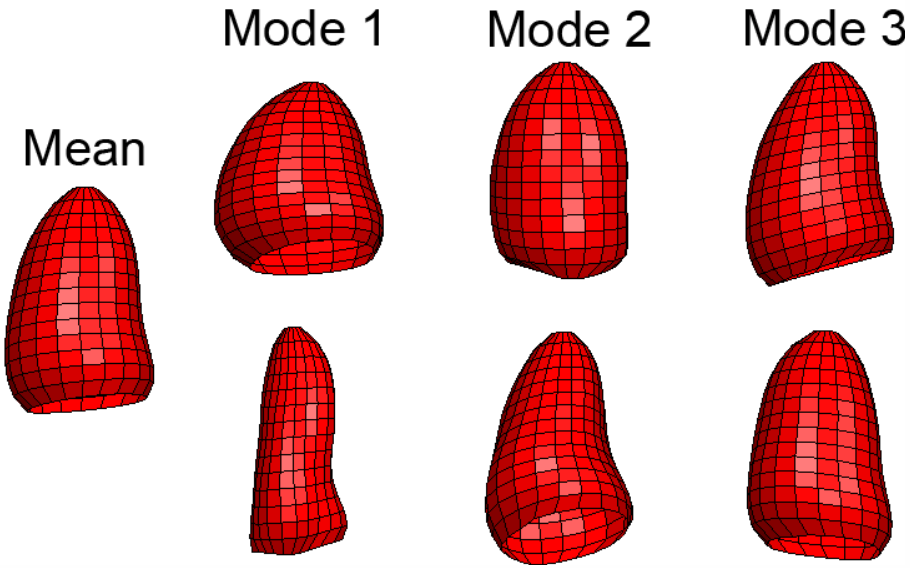
Shape controlled by state $\mathbf{x}_l$

$$\mathbf{q}_i(\mathbf{x}_l) = \bar{\mathbf{q}}_i + \mathbf{A}_i \mathbf{x}_l$$

20 states explains 98% of variation in training set (31 patients).

- Assume deformation in normal direction $\mathbf{n}_i$ to reduce computational cost to 1/3.

$$\mathbf{q}_i(\mathbf{x}_l) = \bar{\mathbf{q}}_i + \bar{\mathbf{n}}_i \cdot \mathbf{A}_i^{\perp} \mathbf{x}_l$$



Deformable model (2/2)

Local transformation

Deformation + Interpolation

$$\mathbf{p}_l(\mathbf{x}_l) = \mathbf{T}_l(\mathbf{q}, \mathbf{x}_l)|_{(u,v)}$$

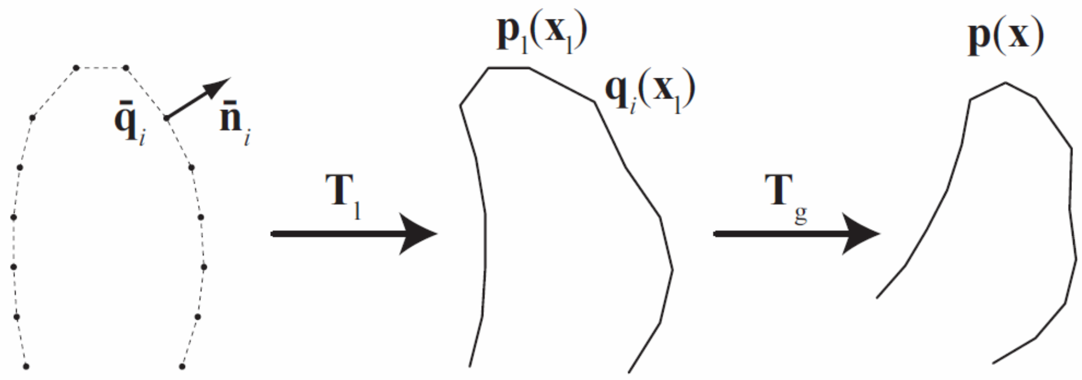
Global transformations

Rotation + Scaling + Position

$$\mathbf{p}(\mathbf{x}) = \mathbf{T}_\mathrm{g}(\mathbf{p}_\mathrm{l}(\mathbf{x}_\mathrm{l}), \mathbf{x}_\mathrm{g})$$

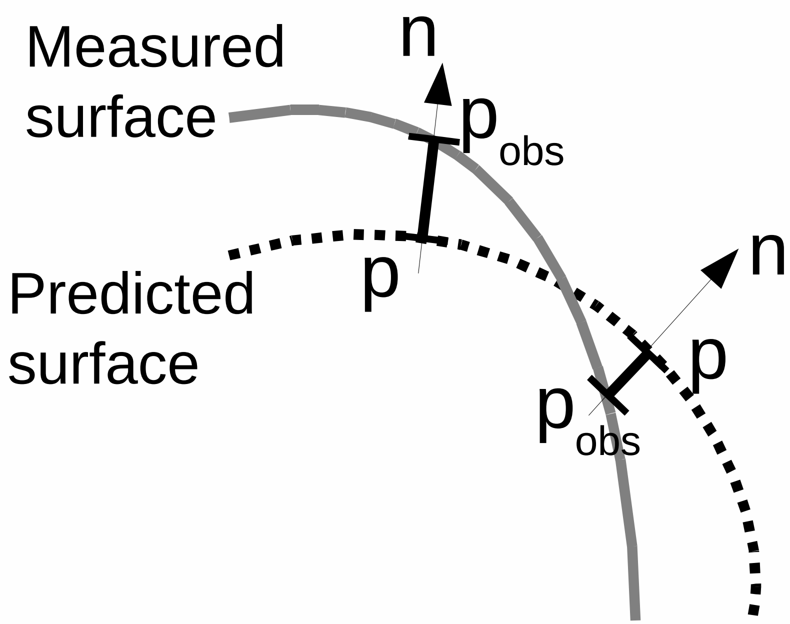
Combined state vector

$$\mathbf{x} = (\mathbf{x}_l, \mathbf{x}_g)$$



Local edge detection

- Perform edge detection in *normal direction* of surface.
- Use *normal displacement* from predicted to measured surface
- Detected edge maximizes intensity transition



Experiments

Setup

Reference: Manually verified surfaces from off-line semi-automated tool, (N=21)

ASM trained on separate population (N=31)

Machine: 2.16 GHz Intel Core 2 Duo.

Initialization

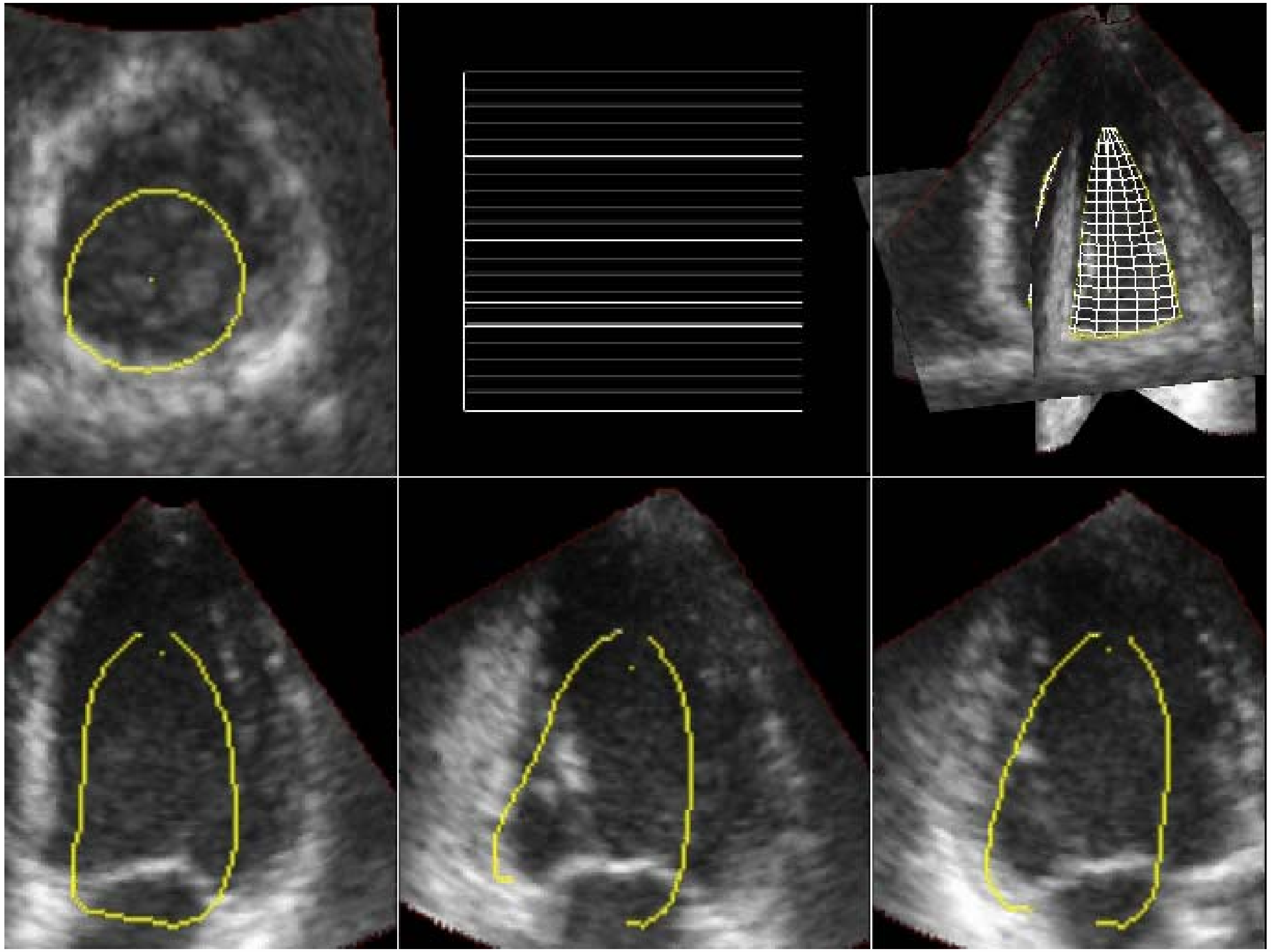
- Average shape/fixed position.
- Track for a couple of cycles to get lock.

Key parameters

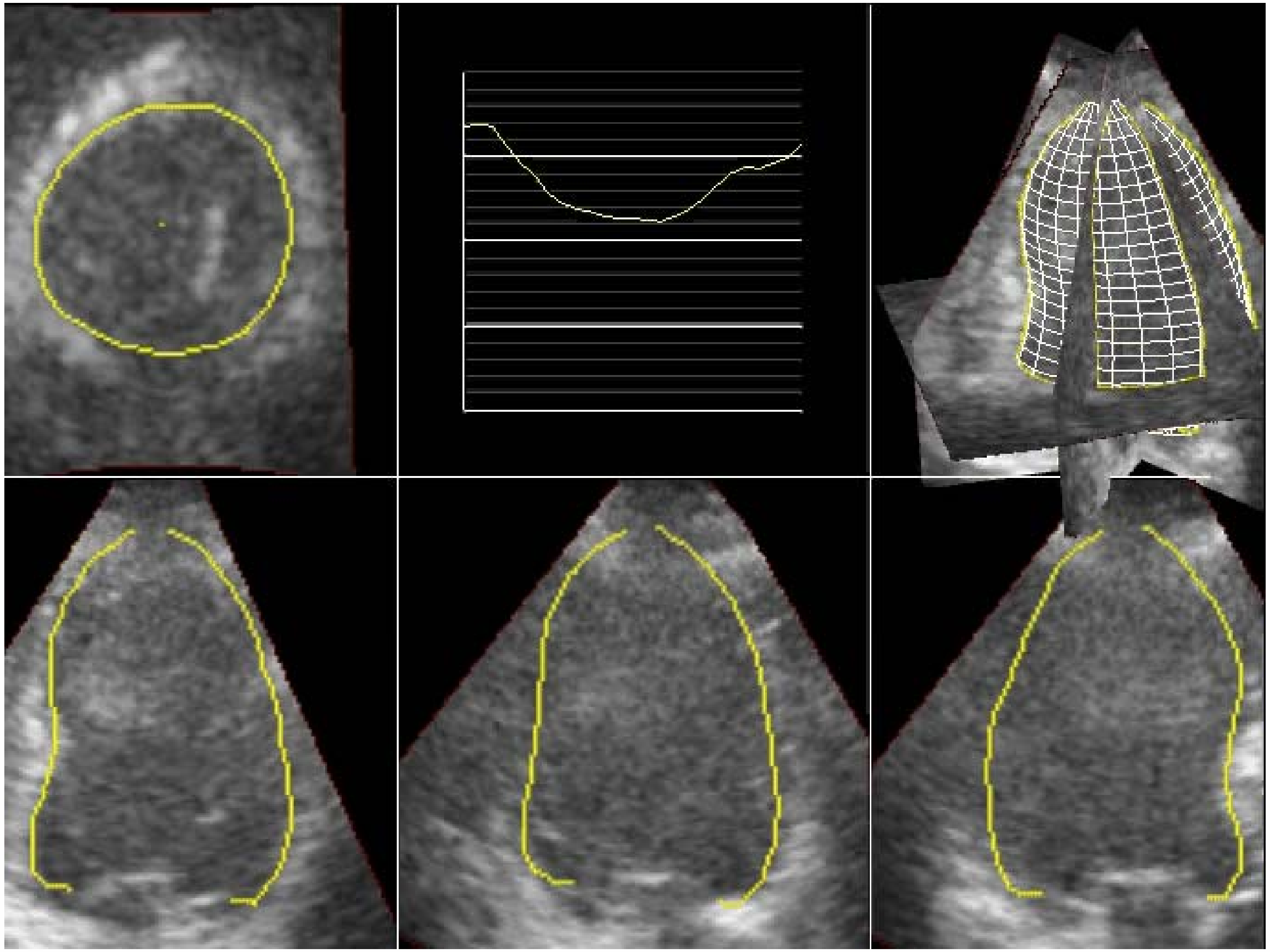
- End diastolic volume (EDV)
- End systolic volume (ESV)
- Ejection fraction (EF)

$$EF = \frac{(EDV - ESV)}{EDV} \cdot 100$$

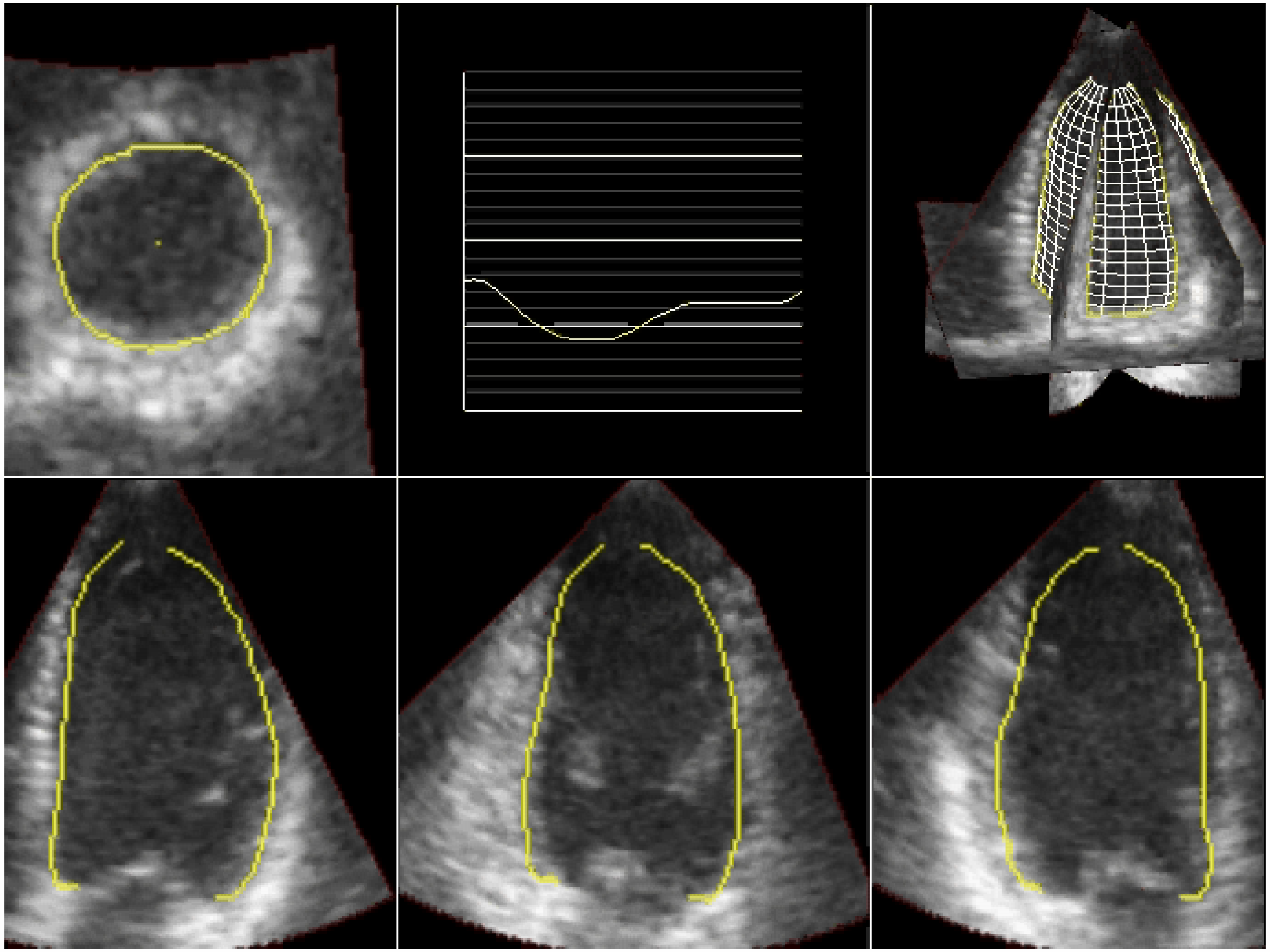
Initialization



Examples (1/2)



Examples (2/2)



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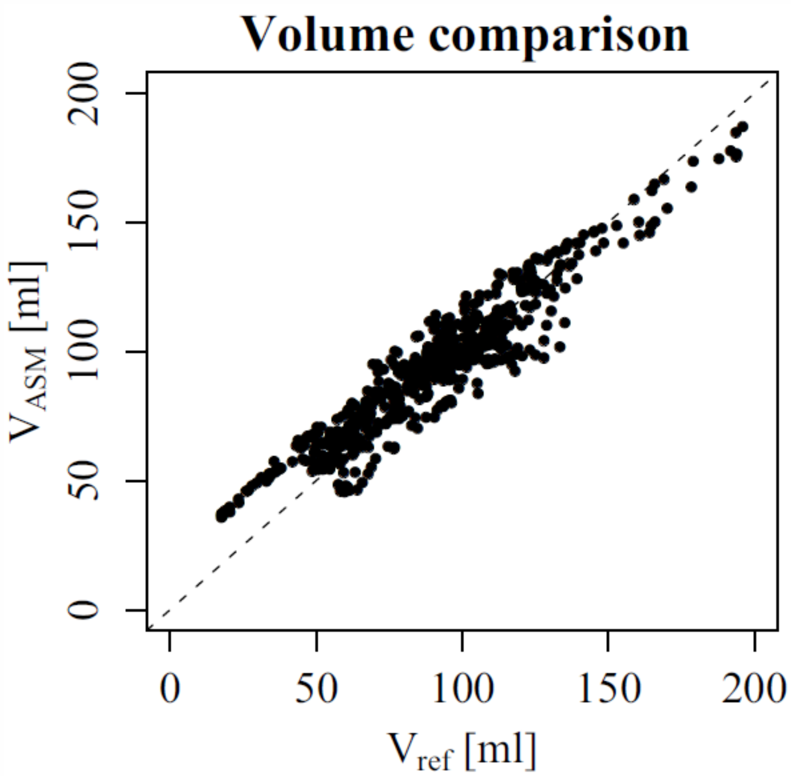
Results

2.2 ±1.1 mm point-to-surface error

Good agreement in volumes and EF

22% CPU load (video rate)



	Volume [ml]	EDV [ml]	ESV [ml]	EF [%]
Difference (mean±1.96SD)	$3.4^* \pm 20$	$-5.9^* \pm 21$	$6.2^* \pm 19$	$-7.7^* \pm 12$
Correlation coeff. (r)	0.95	0.91	0.91	0.74

* Significantly different from 0, $p<0.05$.

Discussion

- Real-time
- Physiologically realistic surfaces
- No user input
- Robust to ultrasound artifacts

- Manual correction difficult
- Missing data problematic
  - Narrow imaging sector
  - Drop-outs

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Conclusion

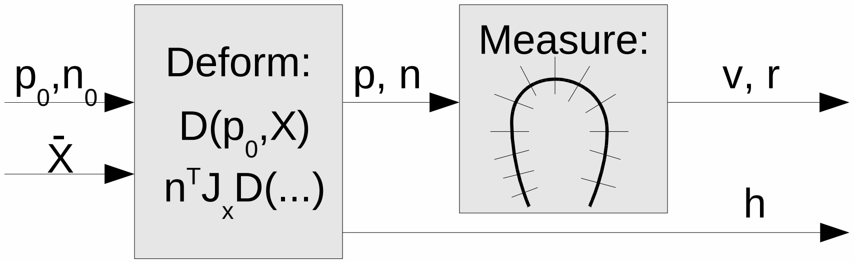
We have developed a fully automatic algorithm for real-time segmentation of the left ventricle in 3D cardiac ultrasound.

Initial evaluation is promising. A larger scale trial is required to evaluate clinical potential.

THANKS!

Measurement sequence

1. Create contour template.
2. Calculate deformed contour, and associated Jacobi matrix based on predicted state.
3. Measure *normal displacements* based on deformed contour.



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Kalman Filter Implementation

Using an *extended* Kalman filter for tracking

- Enables usage of nonlinear deformation models.
- Linearizes model around predicted state.

Kinematic prediction

- Augment state vector to contain state from last two successive frames.
- Models motion, in addition to state/position

Measurement update in information space

- Assumption of independent measurements allow efficient implementation
- Create information-vector and -matrix from measurements
- Use information filter formulation of Kalman filter for measurement update.

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Examples (3/2)