A Deformable Template Model with Feature Tracking for Automated IVUS Segmentation

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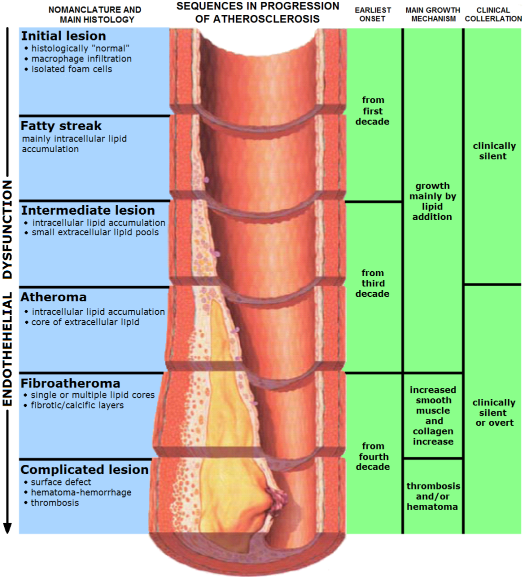
Structure

1. Motivation (2 minutes)
2. Active Contour Models for IVUS (5 minutes)
3. Guidewire Detection and Tracking (10 minutes)
4. Template Model (8 minutes)

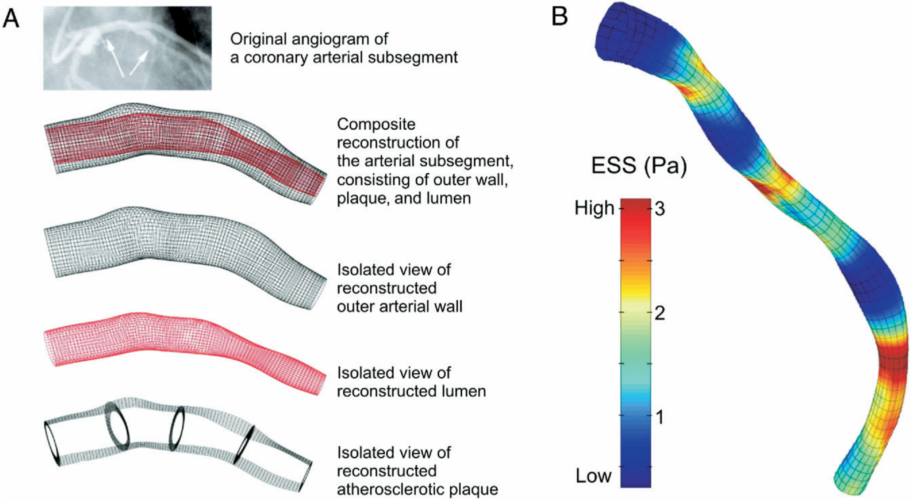
Coronary Heart Disease and Atherosclerosis



- a major cause of death and disability worldwide
- hardening and narrowing of artery due to plaque – macrophases, cholesterol crystals, calcification

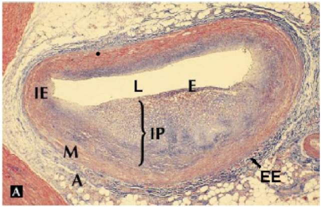
source: Wikipedia Oct 18, 2008
en.wikipedia.org/wiki/Atherosclerotic

Vascular Profiling



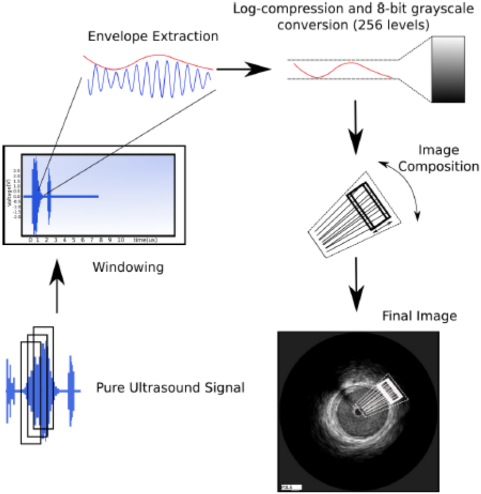
Source: Chatzizisis et. al. *Role of Endothelial Shear Stress in the Natural History of Coronary Atherosclerosis and Vascular Remodeling.* Journal of the American College of Cardiology. Vol. 49, No. 25, 2007.

Histology vs IVUS Image

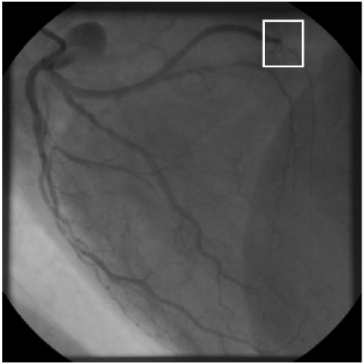


L: lumen E: intima IE: intima IP: intimal plaque M: media A: adventitia EE: external elastic membrane

source: Baggio, Daniel L´elis Intravascular Ultra Sound Image Segmentation Algorithms / Daniel L´elis Baggio. S˜ao Jos´e dos Campos, 2006. 75f. Undergraduate Final Project- Advisor: Prof. Dr. Nei Soma. Co-advisor: Prof. Dr. Sergio Furuie.



Angiography vs IVUS



source: Rotger, D., P. Radeva, C. Canero, et al. 2001. Corresponding IVUS and Angiogram Image Data. COMPUTERS IN CARDIOLOGY: 273-276.

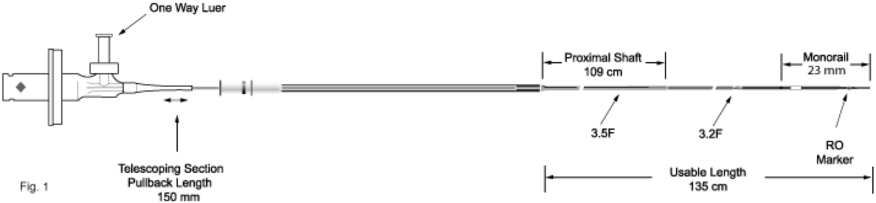
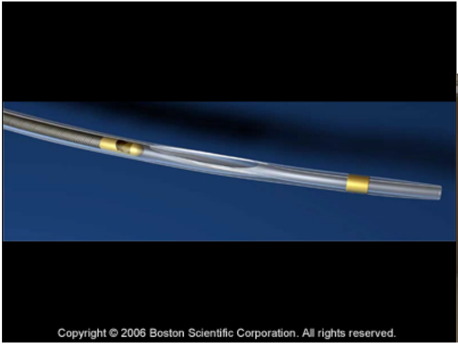
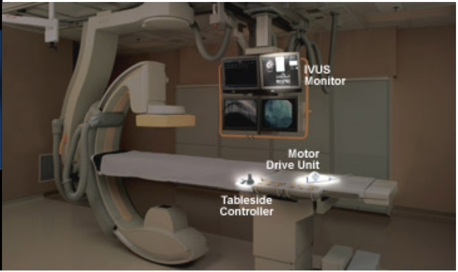


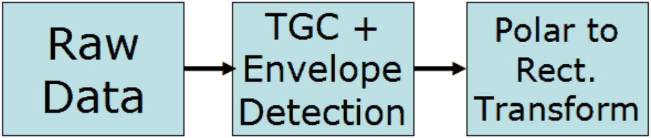
Fig. 1

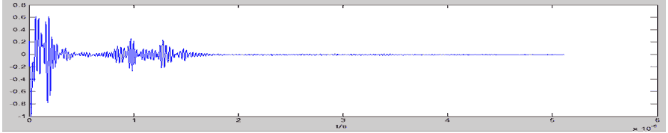




source: Volcano Corporation and Boston Scientific Corporation

IVUS Image Formation





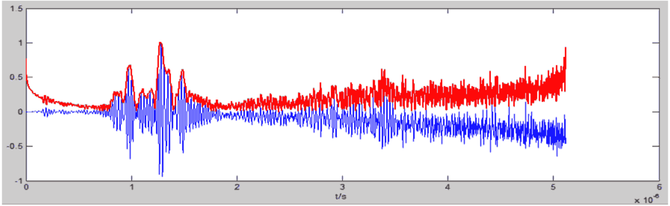
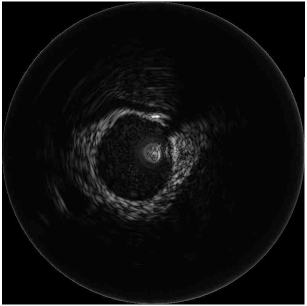
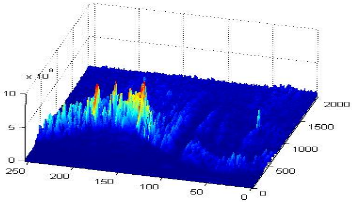
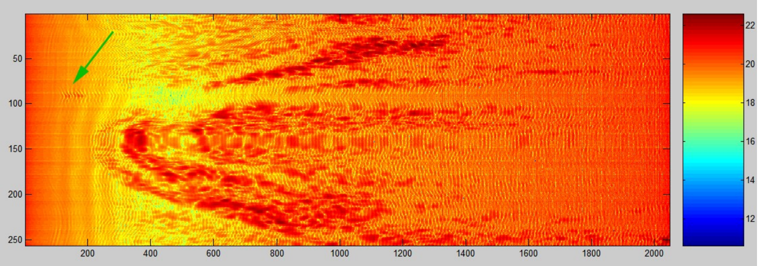


Image Formation (II)







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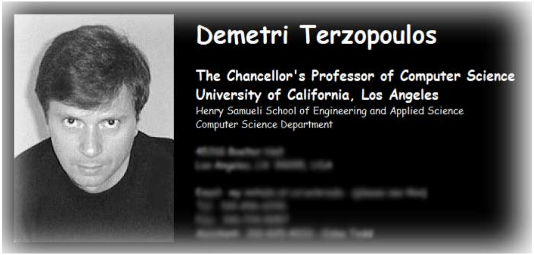
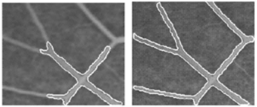
Introduction to Deformable Models



$$
\begin{aligned}
E^*_{\text{snake}} &= \int_0^1 E_{\text{snake}}(\mathbf{v}(s))\, ds \\
&= \int_0^1 E_{\text{int}}(\mathbf{v}(s)) + E_{\text{image}}(\mathbf{v}(s)) \\
&\quad + E_{\text{con}}(\mathbf{v}(s))\, ds
\end{aligned}
$$



- Kass, M., A. Witkin, and D. Terzopoulos. 1988. Snakes: Active contour models. International Journal of Computer Vision 1, no. 4: 321-331.
- Mcinerney, Tim, and Demetri Terzopoulos. 1996. Deformable models in medical image analysis: A survey. Medical Image Analysis 1: 91–108.

Internal, Image and Constraint Energies/Forces

- contour/spline initialization is a separate process
- the contour is iteratively updated by “forces” or “energies”

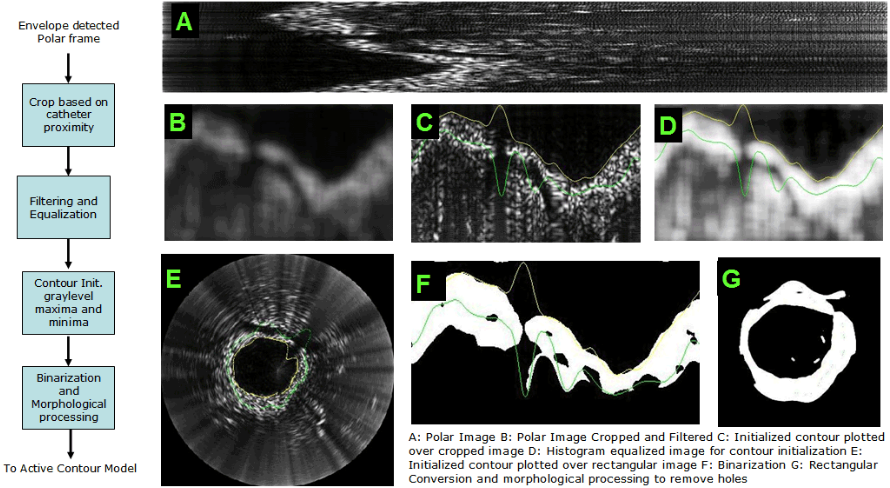
internal forces keep the snake smooth (no abrupt changes and corners in the shape)

image forces (can be based on image gradient or pixel values or other image parameters) make the contour try to follow the image features

external contraints can provide additional forces for the movement of the contour, for example allowing the user to specify where the contour should not wander

First Prototype

contour initialization modified from Giannoglou, G. D., Y. S. Chatzizisis, V. Koutkias, et al. 2007. A novel active contour model for fully automated segmentation of intravascular ultrasound images: In vivo validation in human coronary arteries. Computers in Biology and Medicine 37, no. 9: 1292-1302.



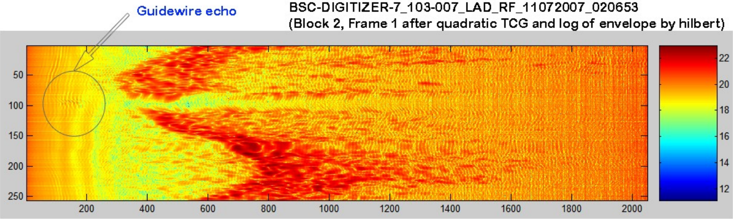
A: Polar Image B: Polar Image Cropped and Filtered C: Initialized contour plotted over cropped image D: Histogram equalized image for contour initialization E: Initialized contour plotted over rectangular image F: Binarization G: Rectangular Conversion and morphological processing to remove holes

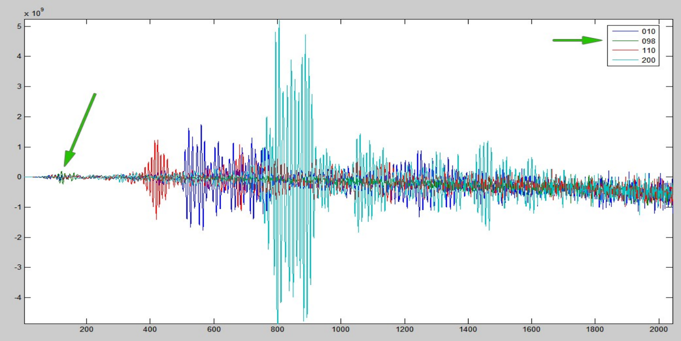
Incorporating Domain Knowledge into ACMs

- artifacts like guidewire are detectable
  - the ACM can simply not use data from these parts
  - or it can intelligently avoid these artifacts and not confuse them with actual features
- lumen boundary should enclose the catheter can be taken into account
- adventitia boundary should enclose the lumen/intima boundaries
- proximity of catheter to the intima wall distorts the image near that area

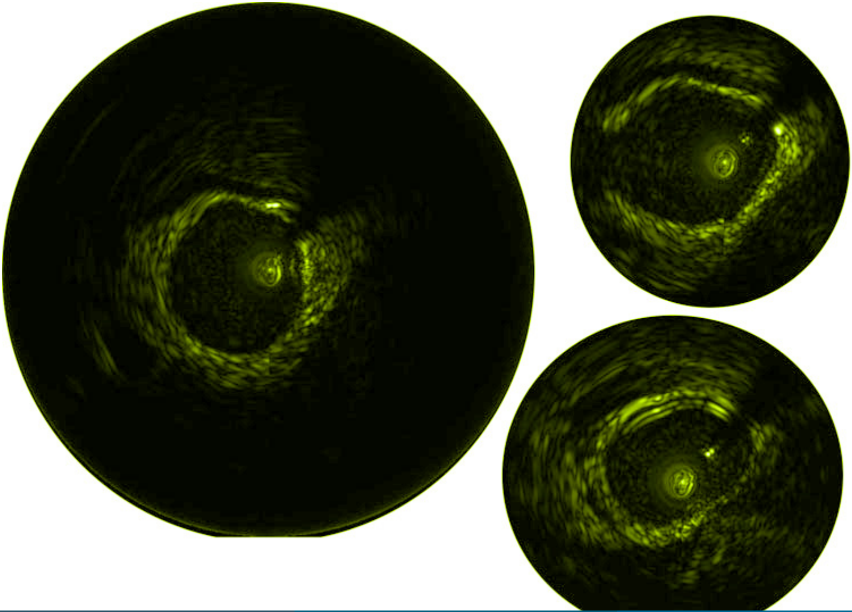
Structure

Problem Definition





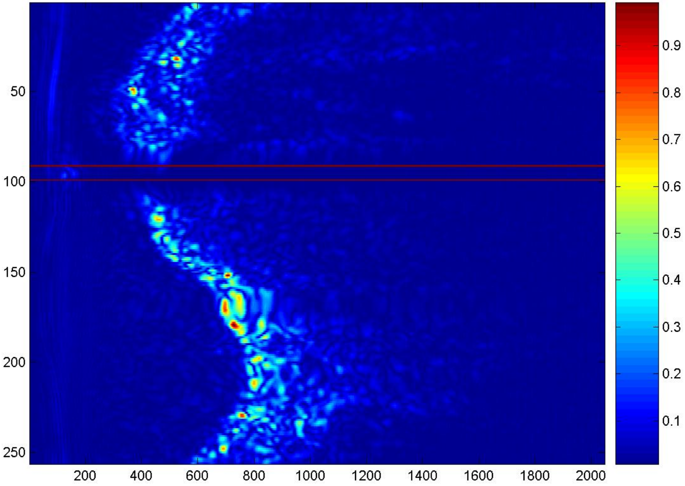
Problem Definition (II)



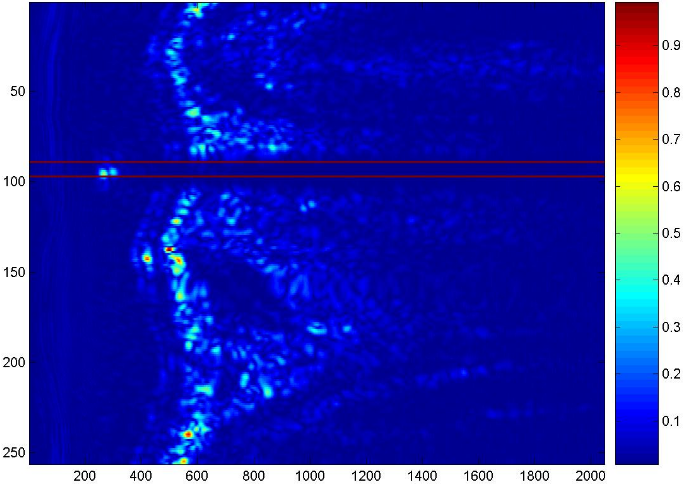
Gaussian Mixture Model Template Matching Algorithm

- the guidewire is modelled as a mixture of two 2D-gaussians (with a width of about 9 vectors)
- several templates are made where the guidewire is placed at various distances from the catheter
- the group of vectors where the difference between the template and the frame data is minimized is chosen as location of the guidewire
- accuracy in the order of 40 frames in 50
- accuracy improved by choosing the 3 candidate minima and then selecting based on voting between frames improves accuracy by a few percent

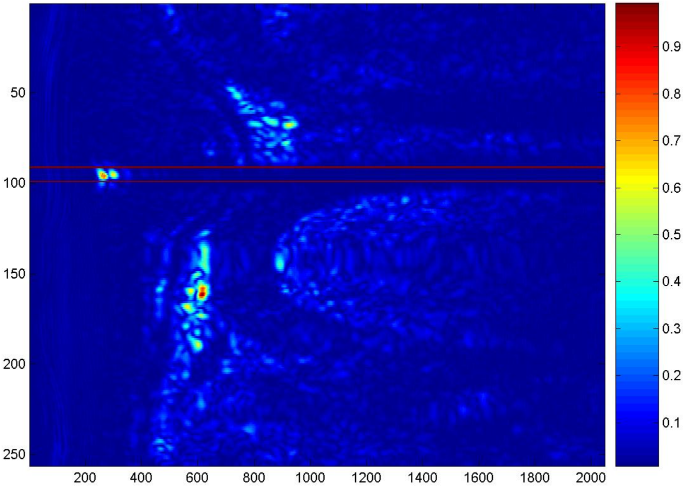
GMM Template Matching Result (I)



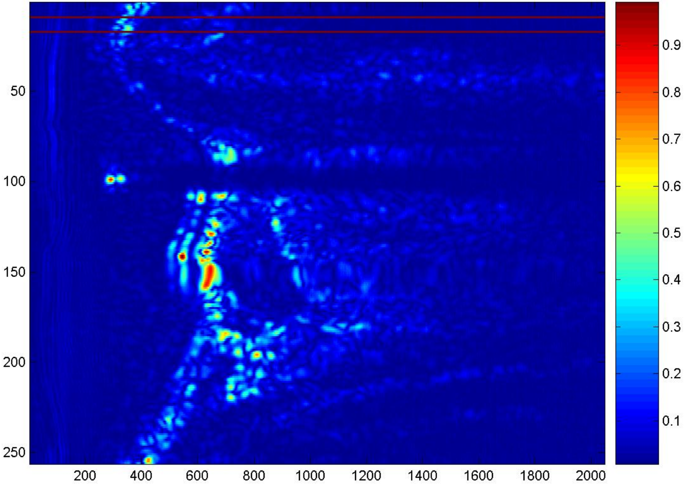
GMM Template Matching Result (II)



GMM Template Matching Result (III)

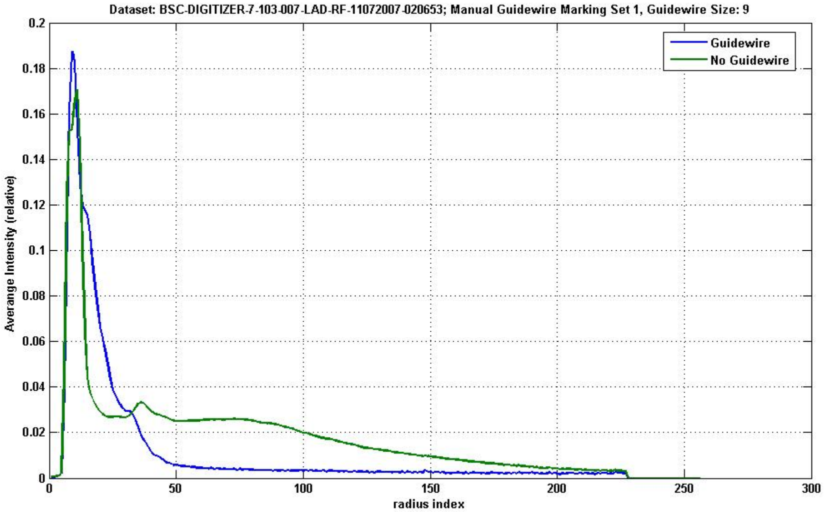


GMM Template Matching Result (IV)



Software for Manual Marking

Guidewire and No-Guidewire Vector Comparison



Tail Energy Ordering Algorithm

$$x_{n,t} = \min_{\theta,n} \sum_{r=r_{min}}^{r_{max}} f(r,\theta);\; n = 1,2,\ldots N$$

where

$f(r,\theta)$ is the image pixel value at radius r and angle θ

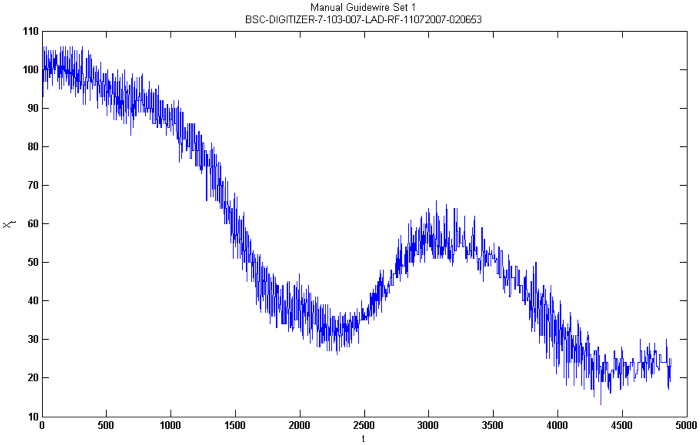
t is the frame index

$x_{n,t}$ is the n^{th} hypothesis that the guidewire is located at $\theta = x_{n,t}$

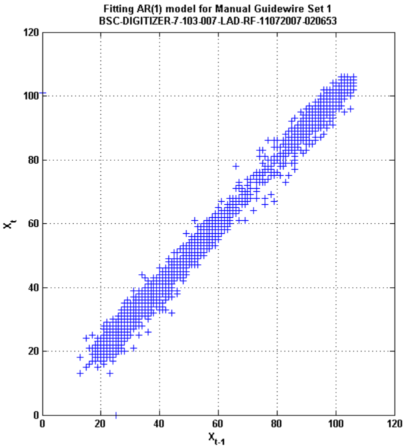
AR-1 Model of Guidewire Position

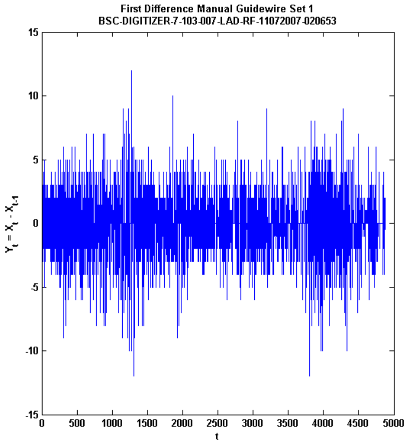
Model

$X_t = X_{t-1} + \varepsilon$

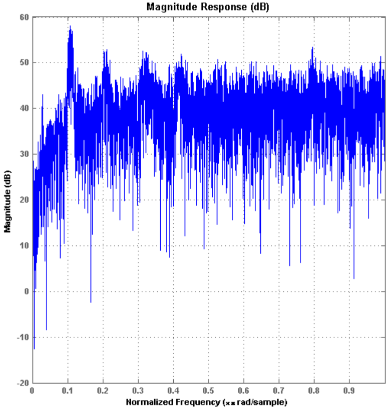


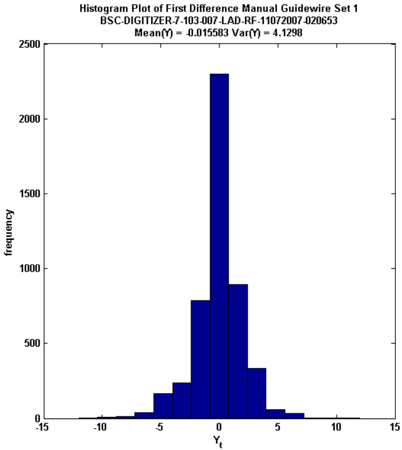
AR1 Model (II)


Fitting AR(1) model for Manual Guidewire Set 1
BSC-DIGITIZER-7-103-007-LAD-RF-11072007-020653
120
100
80
60
40
20
0
0
20
40
60
80
100
120
X_t
X_{t-1}


First Difference Manual Guidewire Set 1
BSC-DIGITIZER-7-103-007-LAD-RF-11072007-020653
15
10
5
0
-5
-10
-15
0
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
$Y_t = X_t - X_{t-1}$
t

AR1 Model (III)





- Kalman tracking with AR1 model?

Tracking features across frames

- dynamic model predicts from the current position at time step (Frame) k of the guidewire – $\hat{\theta}_k$, the position at the next frame $k+1$, $\hat{\theta}_{k+1|k}$
- combined with the N_m "measurements" $\hat{\theta}_{k+1,m}$to produce final estimate $\hat{\theta}_{k+1|k+1}$
- measurements are chosen from most favorable costs (e.g. from the tail-energy ordering algorithm)
- Depending on the tracking algorithm, the measurements are combined with the prediction to form the most likely position for the next frame

state vector $\mathbf{x_k} = [\ \theta_k \quad \dot{\theta}_k\ ]'$,dynamic and observation models:

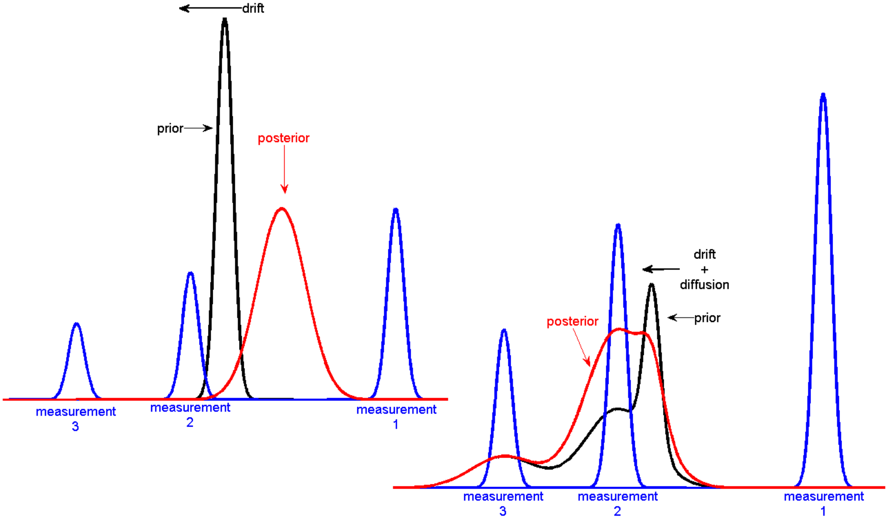
$$
\begin{aligned}
\mathbf{x_k} &= \begin{bmatrix} \theta_k \\ \dot{\theta}_k \end{bmatrix} \\
&= \begin{bmatrix} \theta_{k-1} + \dot{\theta}_{k-1} \\ \dot{\theta}_{k-1} \end{bmatrix} + \begin{bmatrix} n_\theta \\ n_{\dot{\theta}} \end{bmatrix} \\
&= A\mathbf{x_{k-1}} + \xi \\
y_k &= Cx_k + n_o \\
A &= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}; \xi = \begin{bmatrix} n_\theta \\ n_{\dot{\theta}} \end{bmatrix} \\
C &= \begin{bmatrix} 1 & 0 \end{bmatrix}; Q = \begin{bmatrix} \sigma_\theta^2 & 0 \\ 0 & \sigma_{\dot{\theta}}^2 \end{bmatrix}
\end{aligned}
$$

Tracking for each frame k: $\theta_{0(k)}$ is the most favorable measurement

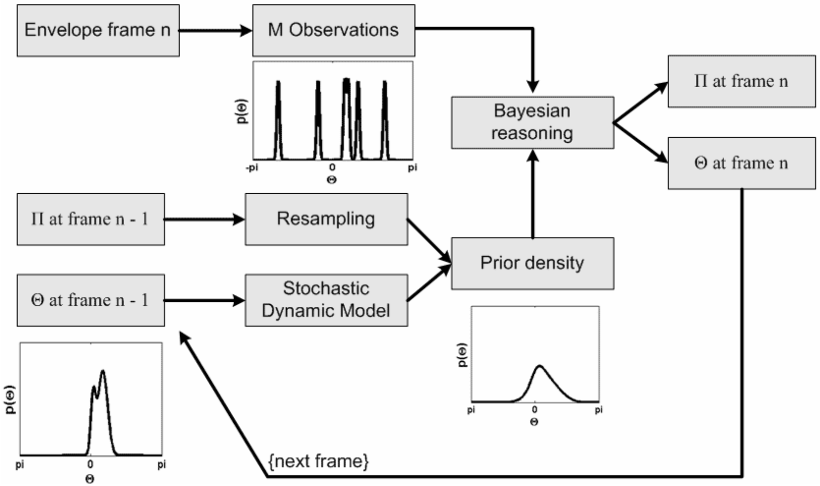
$$
\begin{aligned}
\hat{\mathbf{x}}_0 &= \begin{bmatrix} \theta_{0(0)} & 0 \end{bmatrix}^T \\
P_{0|0} &= Q \\
P_{k|k-1} &= AP_{k-1|k-1}A^T + Q \\
G &= P_{k|k-1}C^T(CP_{k|k-1}C^T + \sigma_o^2)^{-1} \\
P_{k|k} &= (I - G)P_{k|k-1} \\
\hat{\mathbf{x}}_{k|k-1} &= A\hat{\mathbf{x}}_{k-1} \\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + G(\theta_{0(k)} - C\hat{\mathbf{x}}_{k|k-1})
\end{aligned}
$$

Kalman tracking vs. Conditional Density Propagation

Isard and Blake, CONDENSATION—Conditional Density Propagation for Visual Tracking. International Journal of Computer Vision 29(1), 5–28 (1998)

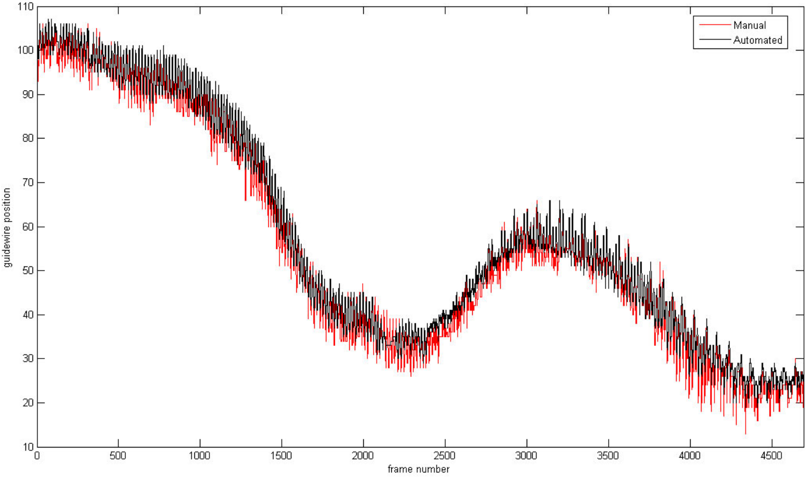


ConDensation (aka. particle filtering; Markov Chain Monte Carlo)



Π : probability weights for parameter values, Θ : parameter values. More details in: Manandhar et. al. *A deformable template model with feature tracking for automated IVUS segmentation* in Handbook of Pattern Recognition 4th Edition. World Scientific, 2010.

Results



Match between ConDensation tracking estimate and manual marked guidewire position.

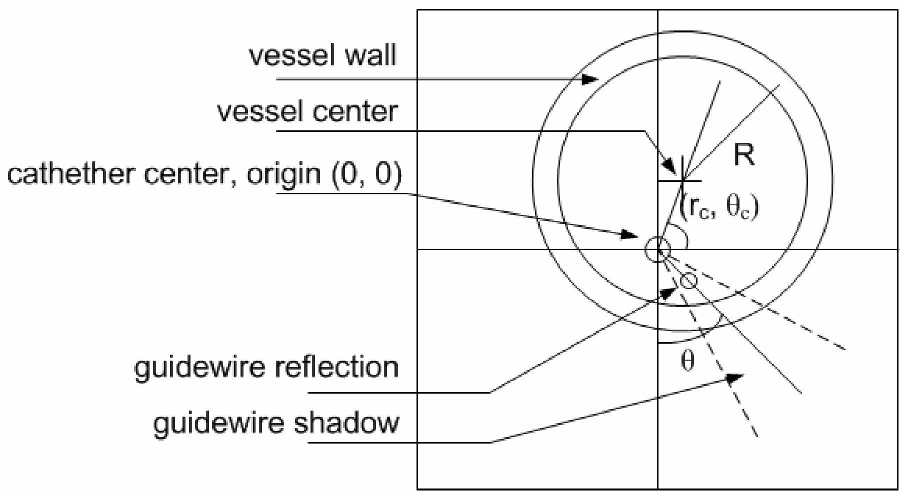
Dataset	Frames	Error >±5					
		BL	KP	KV	PF	PT	PW
1	5211	406	367	490	704	805	494
		7.79%	7.04%	9.4%	13.51%	15.44%	9.48%
2	4691	311	286	389	596	535	275
		6.63%	6.10%	8.29%	12.71%	11.40%	5.86%

Dataset	Frames	Error >±10					
		BL	KP	KV	PF	PT	PW
1	5211	18	3	11	14	28	**16**
		0.35%	0.06%	0.21%	0.27%	0.54%	**0.31 %**
2	4691	88	99	100	136	10	**2**
		1.88%	2.11%	2.13%	2.90%	0.21%	**0.04 %**

BL – baseline algorithm just chooses the best estimate from the observation of the current frame. **KP** – Kalman filtering with position model is a Kalman filter implementation where the next guidewire position is estimated to be the previous position with Gaussian noise. **KV** – similar to KP, but includes a velocity model. **PF** – simple particle filtering without tunneling. **PT** – particle filtering with tunneling. **PW** – particle filtering with tunneling and weighting of observations.

Structure

Tracked Paramters



Contour initialization from Hough Transform

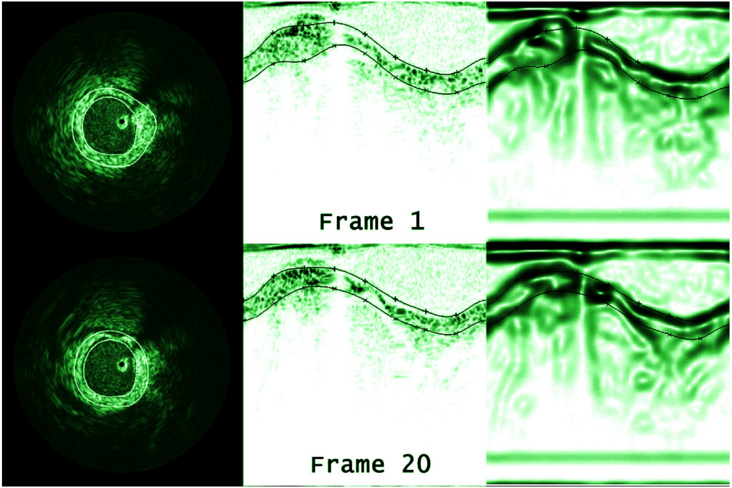
- Estimate: r_c, θ_c, R from pixel values at (r, θ)

$$x = r\cos\theta \qquad y = r\sin\theta$$

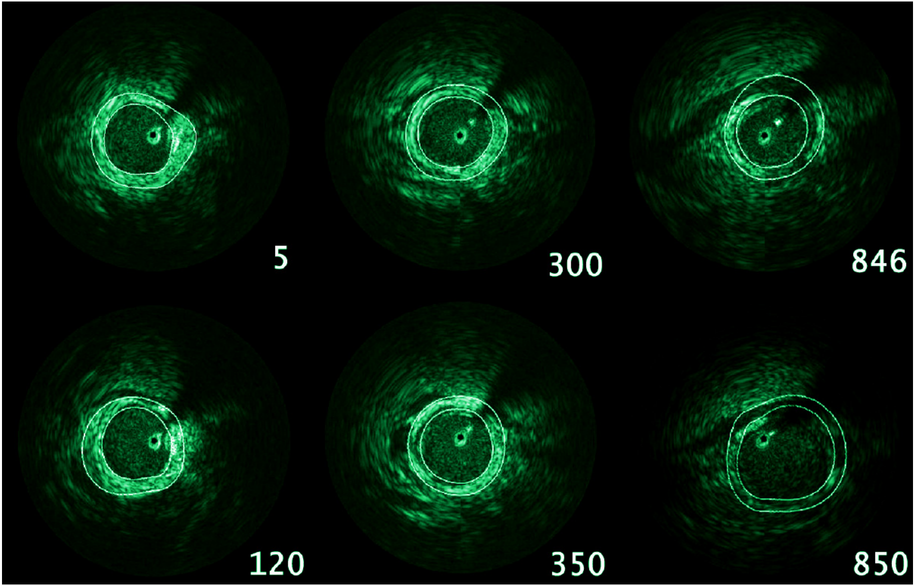
$$\begin{aligned}(x - x_c)^2 &= r^2\cos^2\theta - 2rr_c\cos\theta\cos\theta_c + r_c^2\cos^2\theta_c \\ R^2 &= r^2 + r_c^2 - 2rr_c\cos(\theta - \theta_c)\end{aligned}$$

- Further constraints:
  - $r_{exclude}$ and $\theta_{exclude}$ from guidewire and catheter artifacts
  - $r_c \in [0, 1/2 - \delta], R > r_c + \delta, R + r_c < r_{max}$
- Transform bins have cost function values which are used as "measurements" for ConDensation tracking

Beizer interpolation from control points and Derivative of Gaussian Cost Function



Results



Shoulder Ultrasound

Thanks

- Dr. Charles L. Feldman of Cardiovascular Division, Brigham & Women's Hospital, and and Dr. Ahmet Umit Coskun of Northeastern University, Boston, Massachusetts for providing guidance, reviewing progress and allowing the use of raw and processed data
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- Alan Solomon, M.D. for providing me with shoulder ultrasound data

Thank you for listening

Questions?