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Image-Based tracking technologies - Tutorial of Image guided interventions

Terrence Chen, PhD
Program Manager
Video Analysis & Understanding

Image Analytics and Informatics
Siemens Corporate Research
Princeton, NJ

with contributions from Siemens
colleagues and clinical collaborators



Outline

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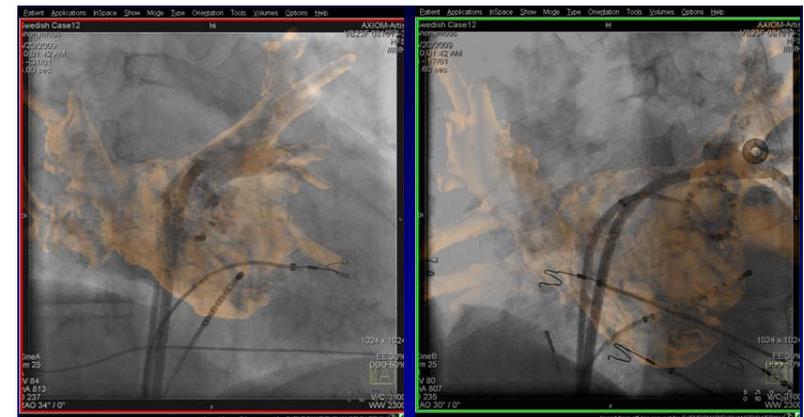
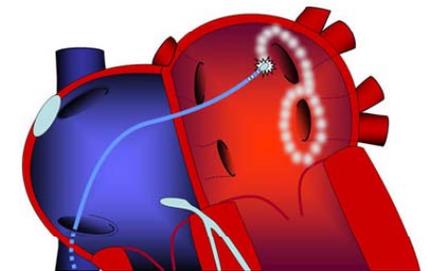
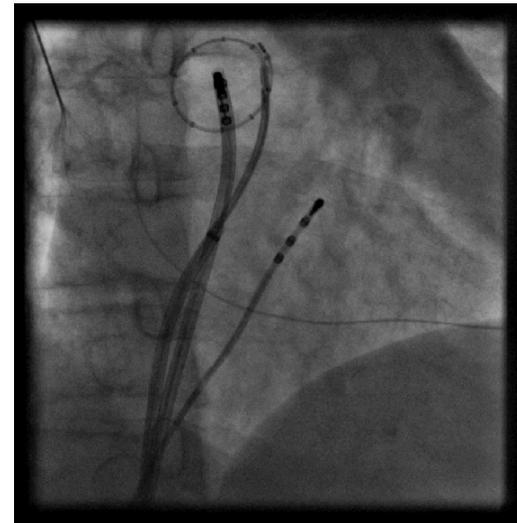
- **Why tracking?**
- **Challenges**
- **Existing work**
- **Tracking by robust detection**
- **Conclusion**

Why tracking?

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- Track the position of instruments/devices relative to the patient anatomy.
- Guidance
 - Motion compensation
 - Positioning & Navigation
 - Planning
 - Enhancement
 - Registration
- Methods
 - Hardware
 - Mechanical, Optical systems
 - Electromagnetic tracking
 - Software
 - Image-based tracking technologies



Electromagnetic v.s. Image-based

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- Electromagnetic tracking
 - Expensive
 - Limited availability
 - High accuracy and robustness
 - Clinical usage – getting popular
- Image-based tracking
 - Cheap
 - Simple
 - Need to deal with high data variation
 - Need to acquire representative amount of data
 - High performance requirement for a practical clinical solution
 - Clinical usage – currently very limited

Challenges

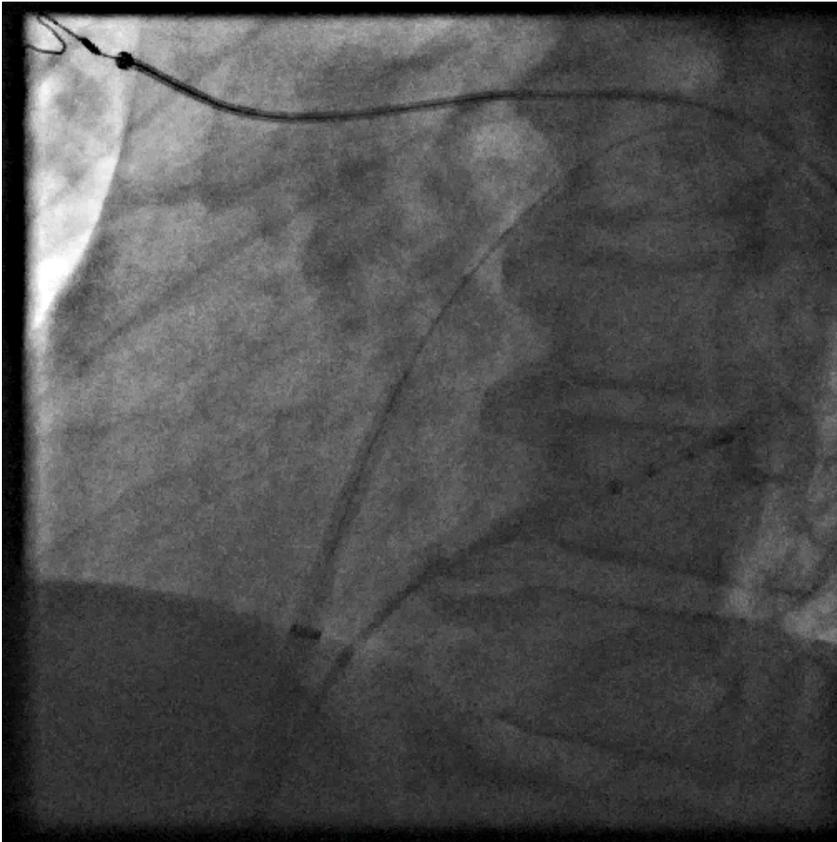
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- **Typical challenges in visual tracking -**
 - Low image quality, heavy noise, low SNR
 - rapid motion
 - Non-rigid object : catheter with non-rigid deformation
 - Foreshortening due to projection
 - Occlusion & overlapping by other catheters or background artifacts
 - Target object moves in and out of the ROI
 - Multiple objects – track multiple catheters simultaneously
 - High speed requirement
- **More –**
 - Tons of other challenges for specific applications

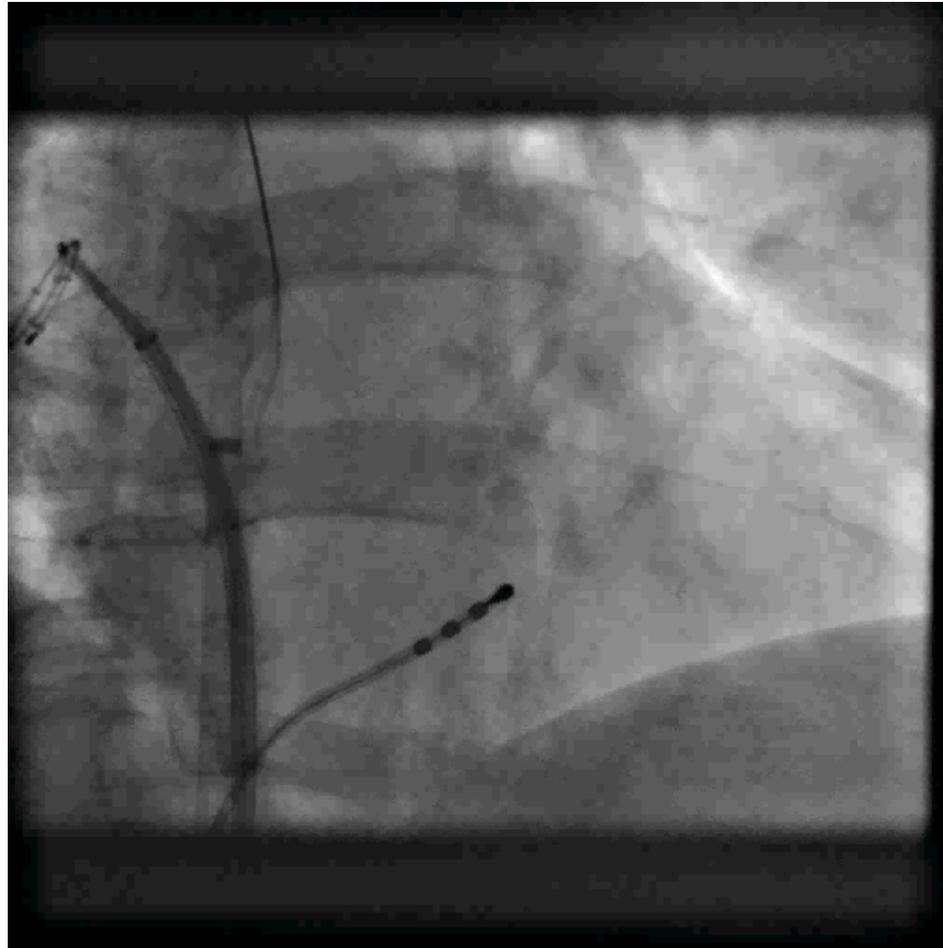
Data with heavy noise (low SNR)

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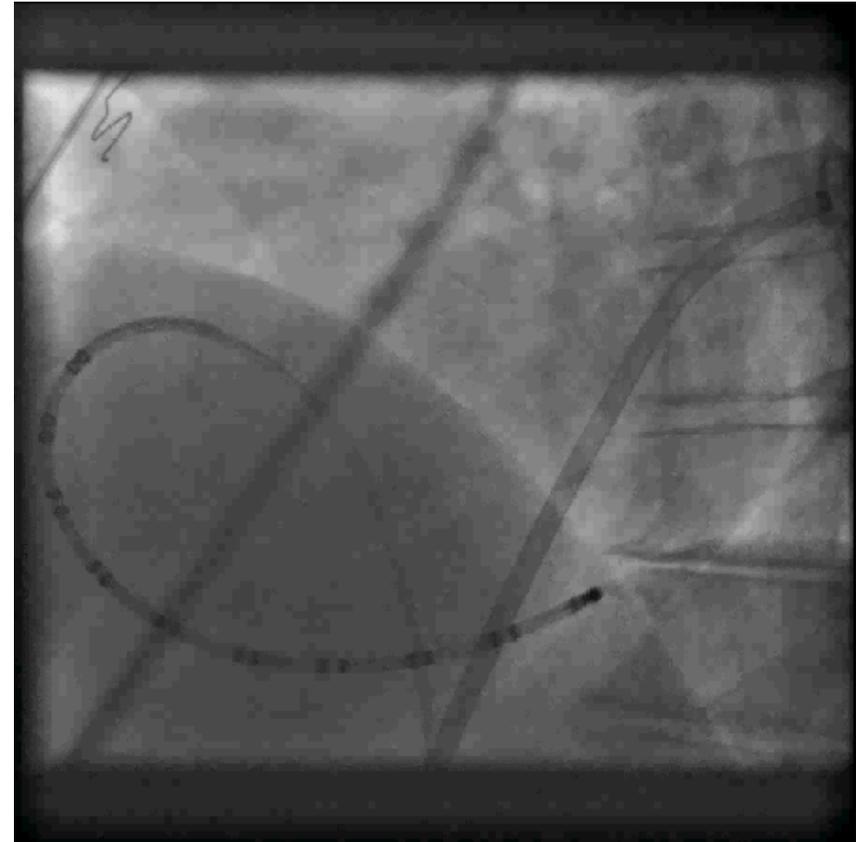
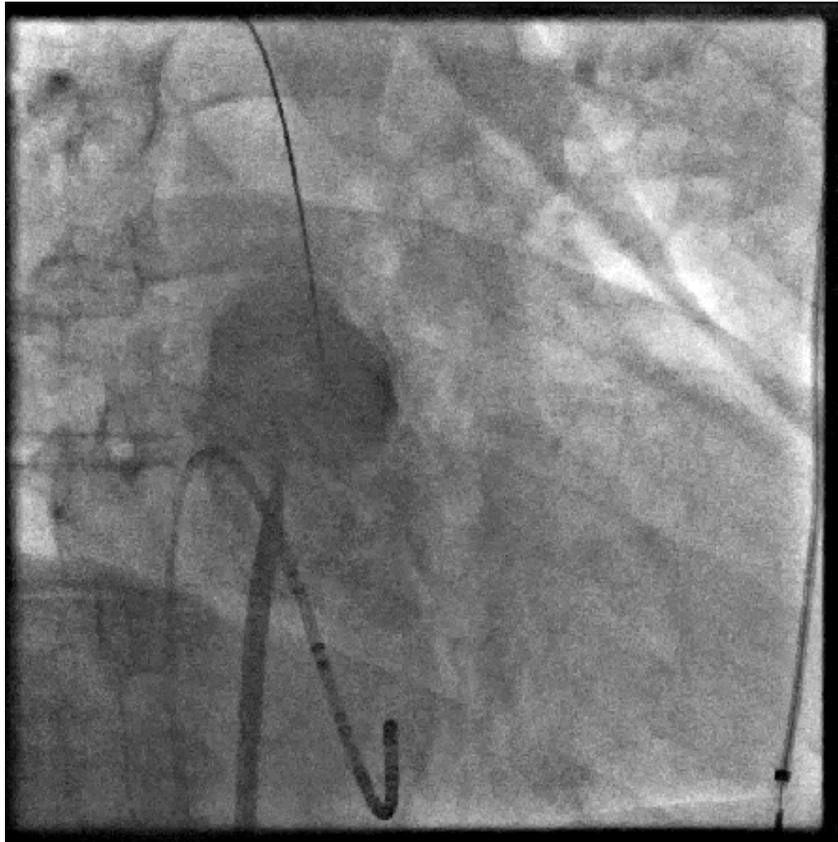
rapid motion

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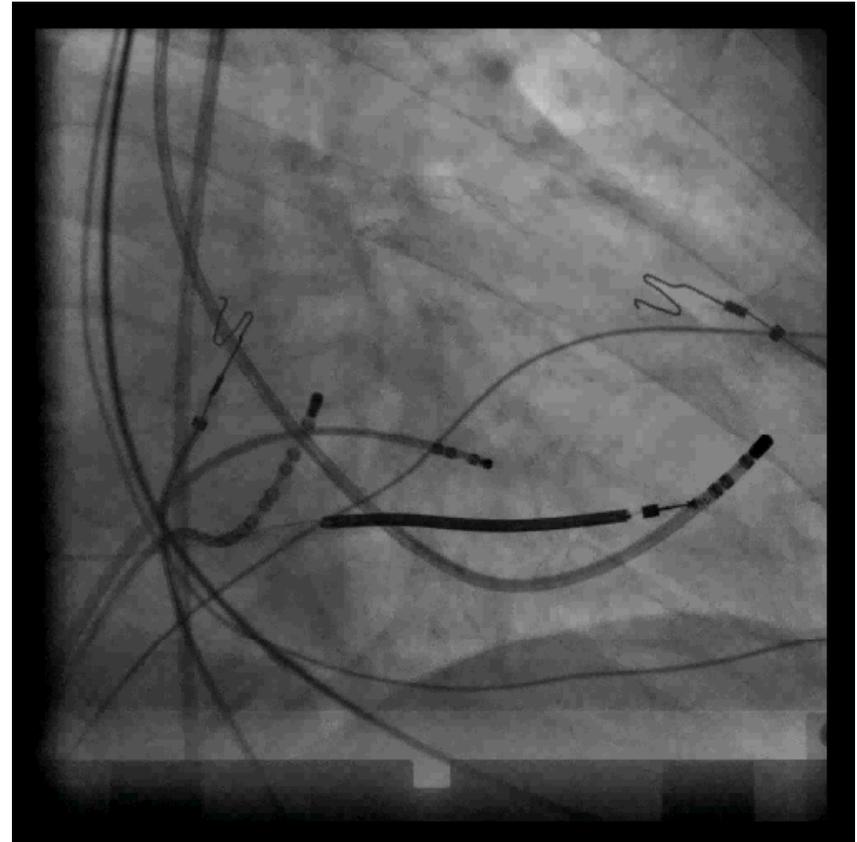
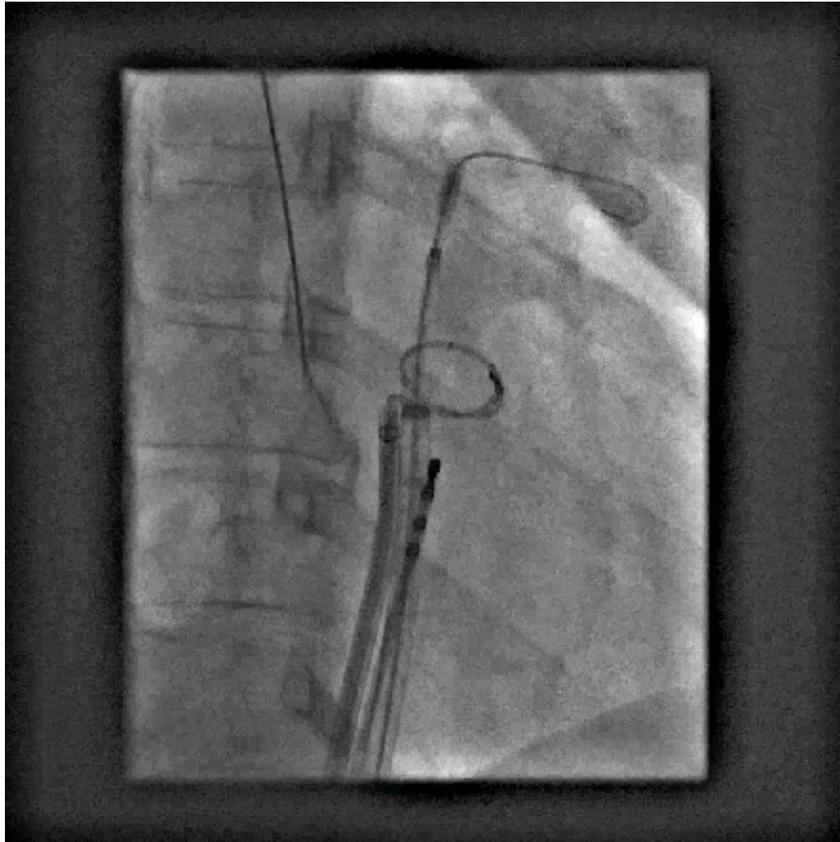
Long catheter with non-rigid deformation & foreshortening

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Overlapping catheters and artifacts

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Part or full of the catheter close to image border and moves in & out

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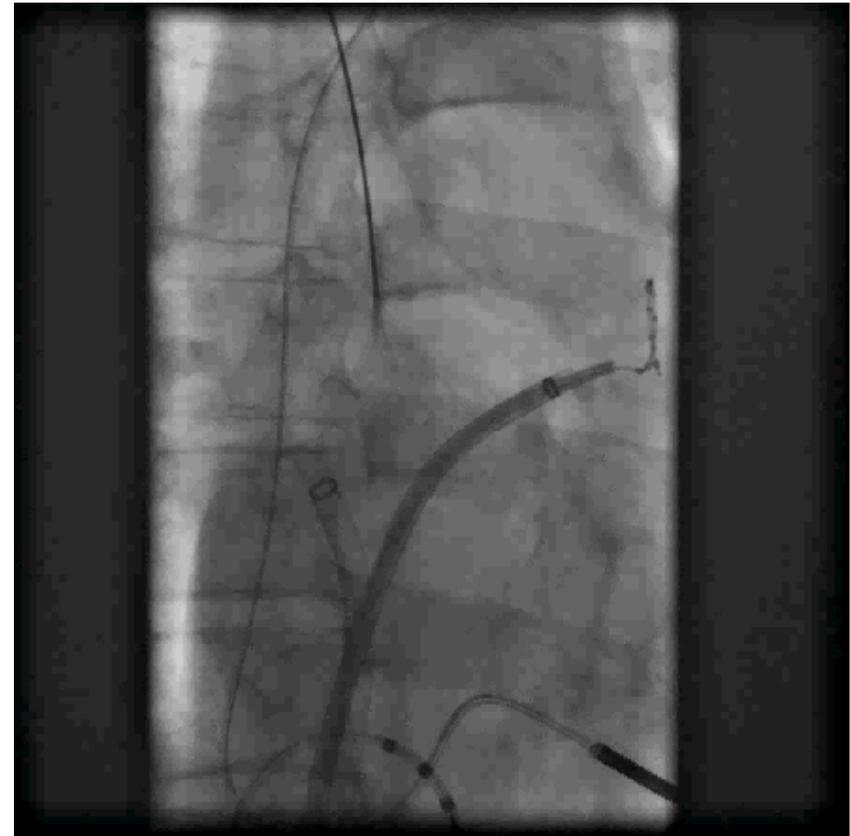


Image-based tracking technology

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- **Needle – rigid wire**
 - Atasoy et al. SPIE Medical Imaging, 2008
 - Heibel et al. ISBI, 2010
- **Guide-wire**
 - Palti-Wasserman et al. Trans. Bio. Eng. 1997
 - Baert et al. TMI 2003
 - Slabaugh et al. MICCAI 2007
 - Heibel et al. CVPR 2009
 - Petkovic et al. ISBI 2010
- **Different types of catheters**
 - Ma et al. MICCAI 2010
 - Brost et al. MIA 2010
- **Common points for the existing state-of-the-art**
 - Most work is after 2007 – the field is relatively new and growing
 - Evaluated on a very limited dataset – a few only evaluated on 1 data sequence

Image-based tracking technology

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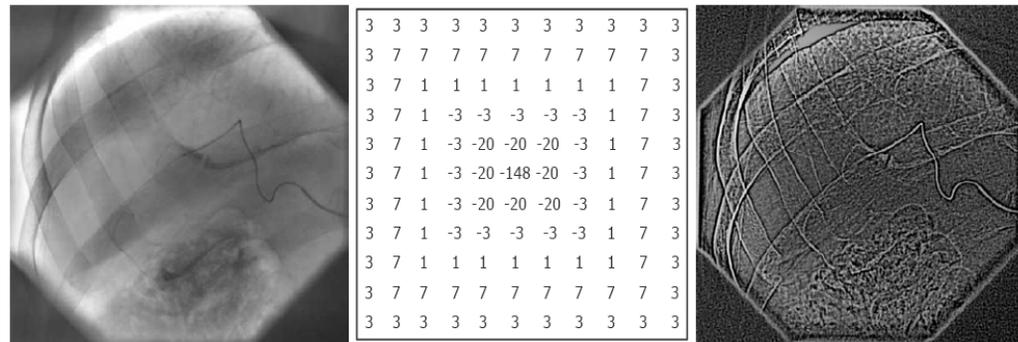
Needle – rigid wire tracking

Atasoy et al. SPIE 2008

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- Step 1 : Apply a filter (Marr-Hildreth filter) to enhance the line structure up to 5 pixels

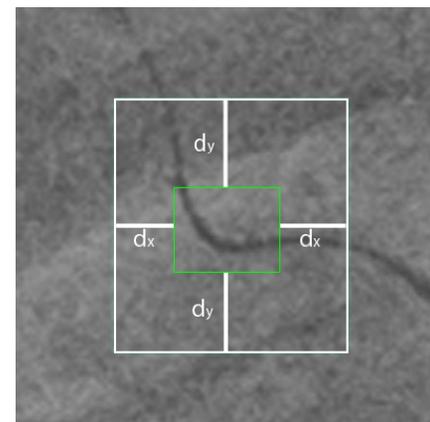


- Step 2: Tracking by template matching
 - Using correlation coefficient as a similarity metric to find the best match image patch at time $t+1$ to the image patch at time t

- Step 3: Dynamic template update

Results:

- On 4 real sequences
- Average error: 1.25 mm, std: 0.44 mm
- The catheter needs to be curvy
- The deformation and displacement of the catheter needs to be small



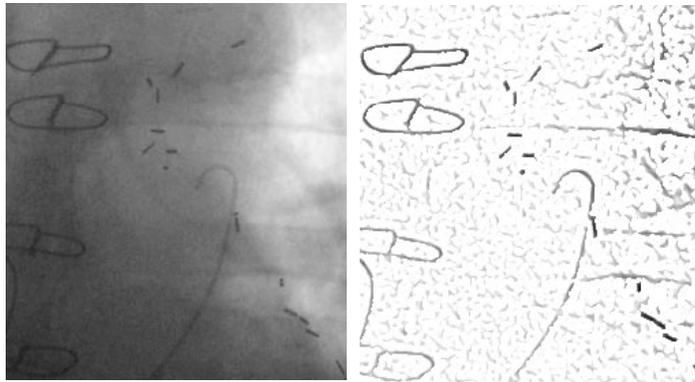
Guidewire tracking

Baert et al. TMI 2003

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- **Step 1: Rigid translation**
 - Highest cross-correlation in the feature space within a search range
 - The eigenvalues of the Hessian matrix



- **Step 2: Spline optimization**
 - Internal & external force
 - Internal – first derivative & second derivative of the spline
 - External – feature image values
- **Results: 141/146 frames from 5 image sequences**
- **Wire is only a short piece, which is the most visible part of the wire**
- **Compare this line feature to image intensity and subtraction images**

Guidewire tracking

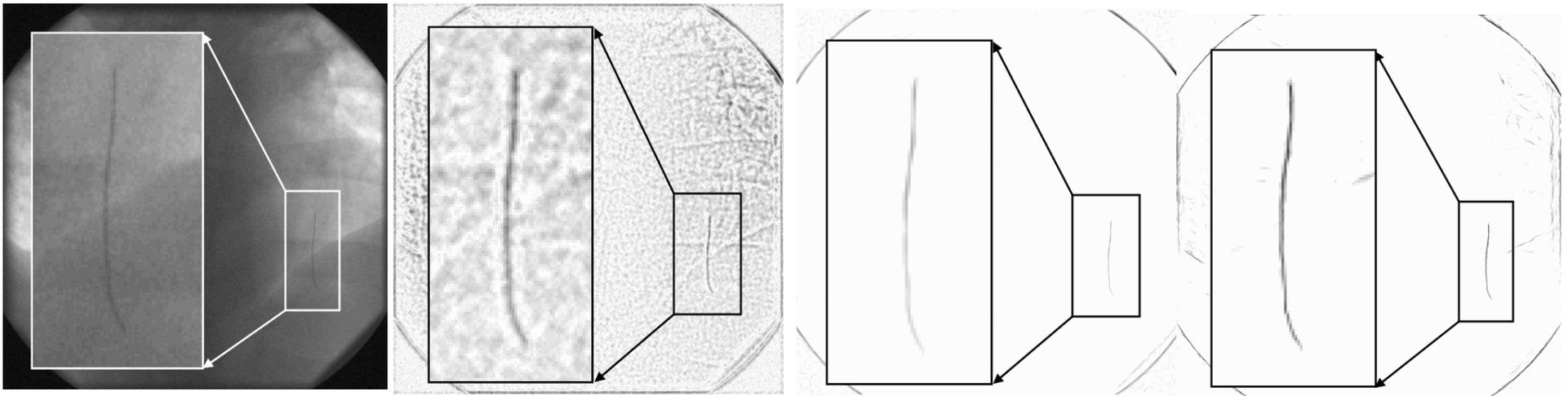
Slabaugh et al. MICCAI 2007

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- **Step 1: Rigid translation**

- Phase congruency as image features – log Gabor functions over multiple scales and orientations



- **Step 2: Spline optimization**

$$E(C) = w_1 \cdot \text{data} + w_2 \cdot \text{smoothness} + w_3 \cdot \text{length constraint}$$

$$= w_1 \int_C F ds + w_2 \int_C ds + w_3 \left(\int_C ds - L_0 \right)^2,$$

- **Results: 148/158 frames from 5 image sequences**
- **Similar to Baert et al 's work**

Guidewire tracking

Heibel et al. CVPR 2009

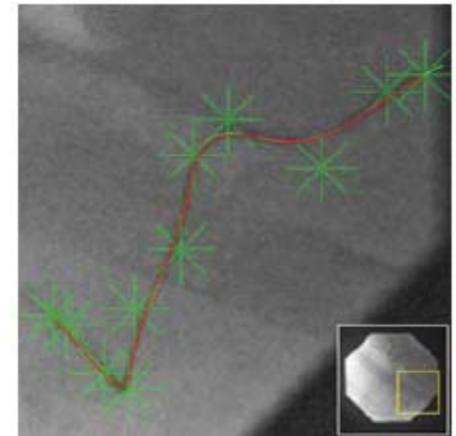
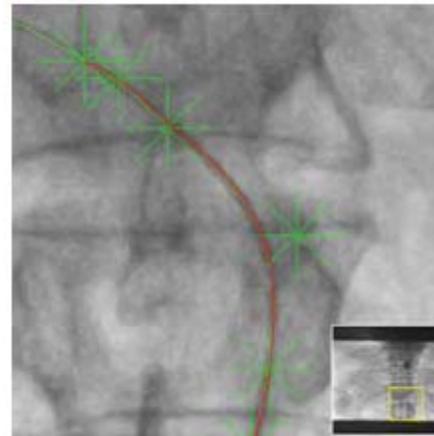
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- Guidewire model – B-spline curve
- Each control point is associated with a random variable in a MAP-MRF formulation
- A set of labels capture the deformation space
- Tracking is to find the optimal configuration of the control points

$$C(s) = \sum_{i=1}^M N_i(s)P_i \quad \text{where } s \in [0; 1]$$

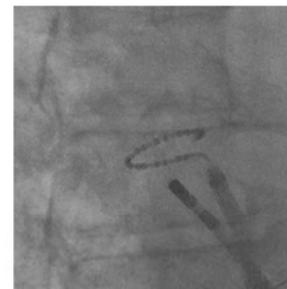
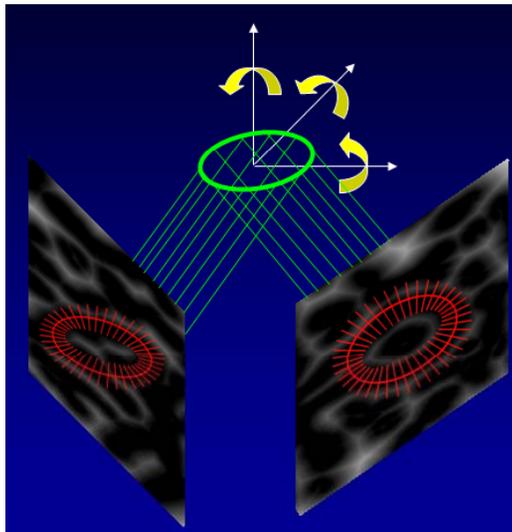
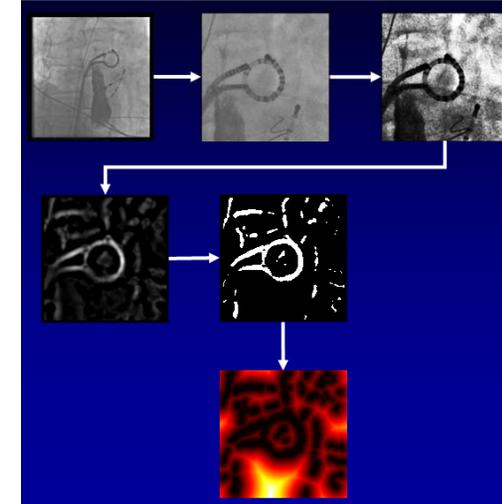
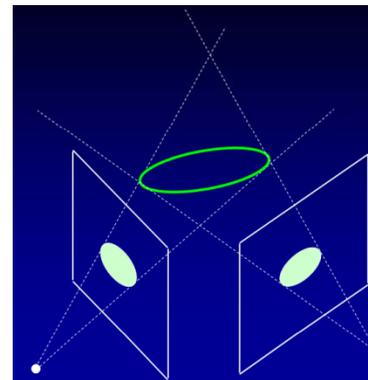
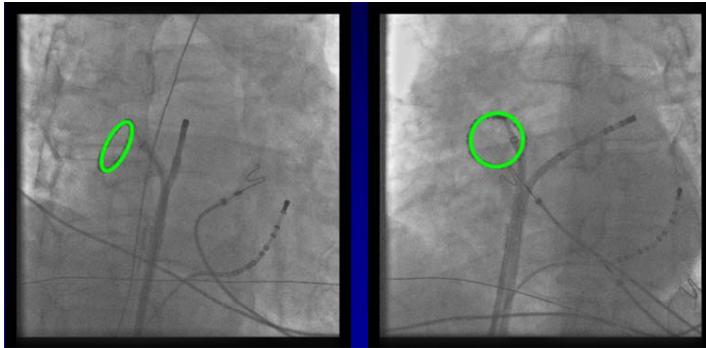
- Results: 2 clinical sequences with 142 and 228 frames



Catheter Tracking

Brost et al. – circumferential mapping catheter

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(a) ROI



(b) Filtering



(c) Classification

- Evaluated on 13 sequences with good results
- Constraint: Bi-plane system required

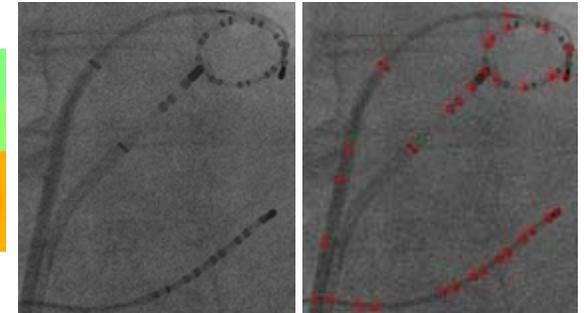
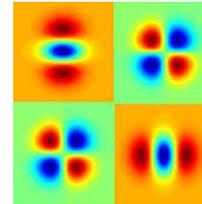
Catheter Tracking

Ma et al – CS catheter tracking

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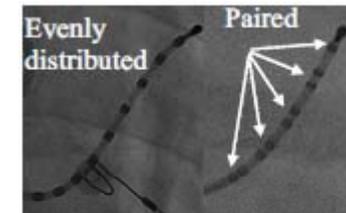


- Step 1: Blob detection
 - Multi-scale blob detector based on the determinant of the Hessian matrix



- Step 2: Catheter detection

$$CSCathCost = \frac{\sum_{i=1}^{N-2} |\cos \theta_i - \overline{\cos \theta}|}{N-2} + \frac{\sum_{i=2}^N |Blob_i - \overline{Blob}|}{N-1}$$



- Results: 18 sequences, 1048 frames

Electrode	1	2	3	4	5	6	7	8	9	10
Low dose images	0.4	0.6	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Normal dose images	0.4	0.8	0.3	0.4	0.3	0.3	0.4	0.4	0.3	0.3

- Constraints:

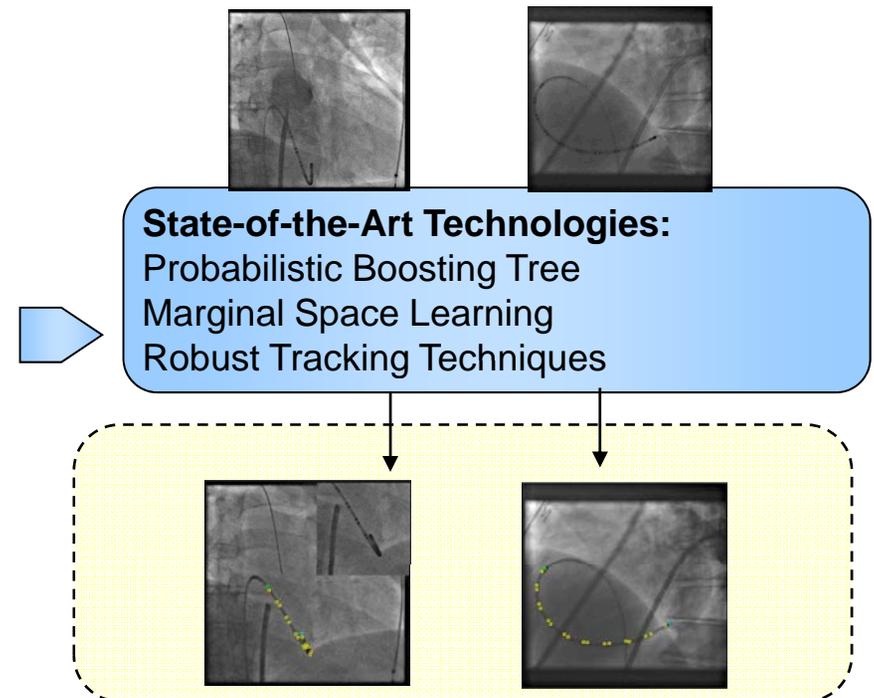
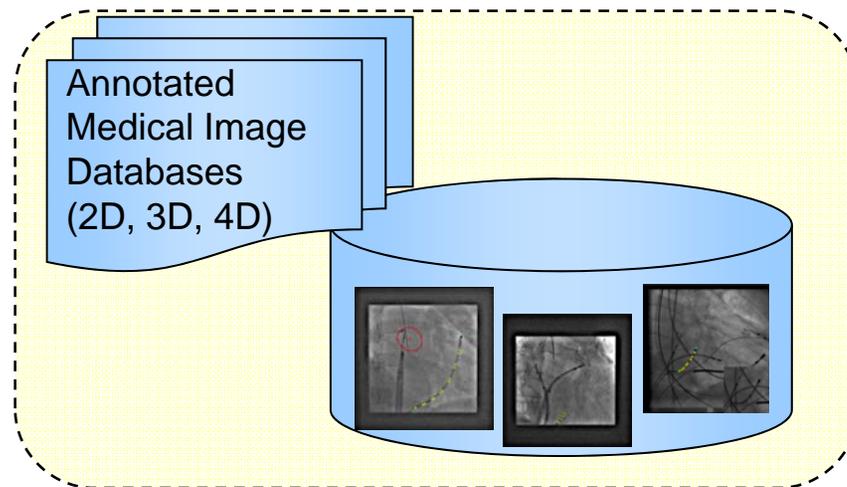
- Catheter has to have fixed # (10) of electrodes,
- Catheter cannot bend over 90 degree (foreshortening)

Our methodology - Tracking by robust detection

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- Key technologies
 - Machine learning-based detection for different devices, such as guidewire, needle, marker, electrode, catheter, etc.
 - A Bayesian inference framework - a probabilistic framework to fuse different hypothesis and cues, including detection response, and image appearance
 - Multi-hypothesis tracking
 - Hypothesis fusion
 - Online Model updating
 - Online learning

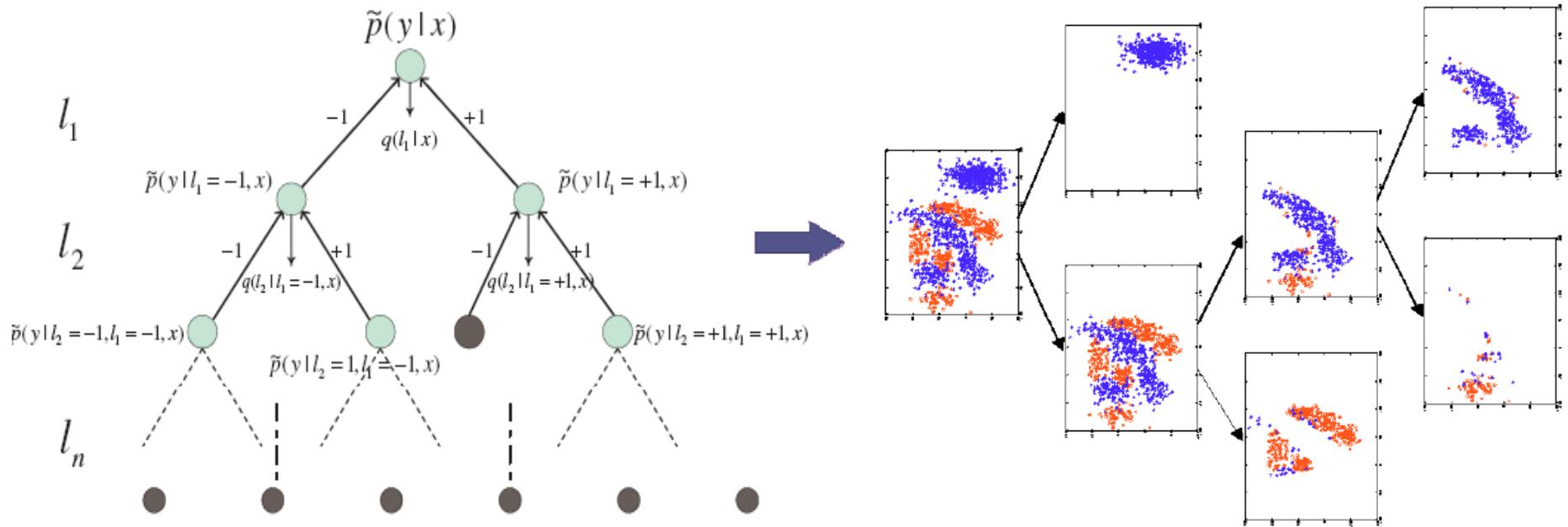


Probabilistic Boosting Tree (PBT)

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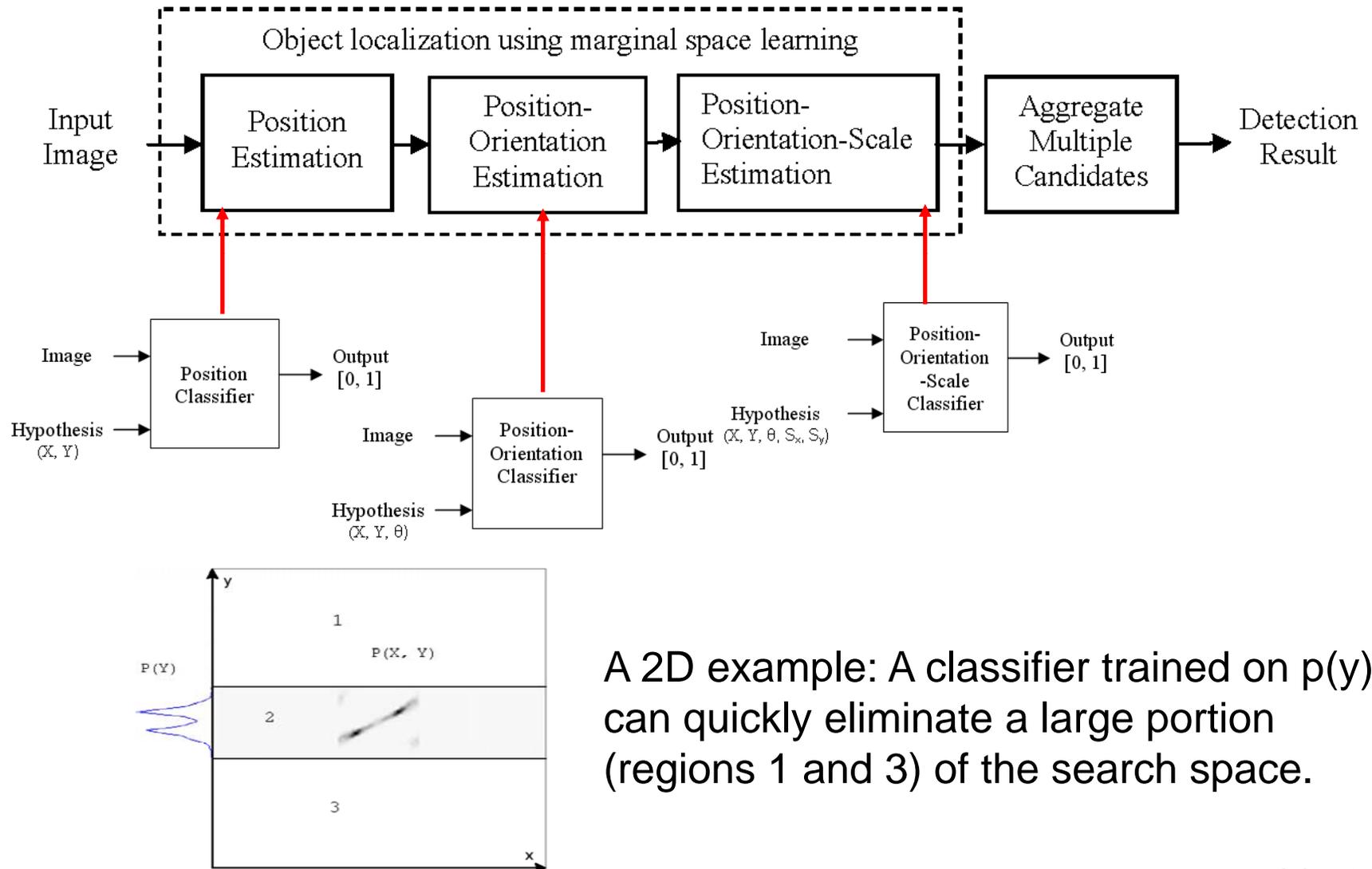


- The probabilistic Boosting Tree



Marginal Space Learning (MSL)

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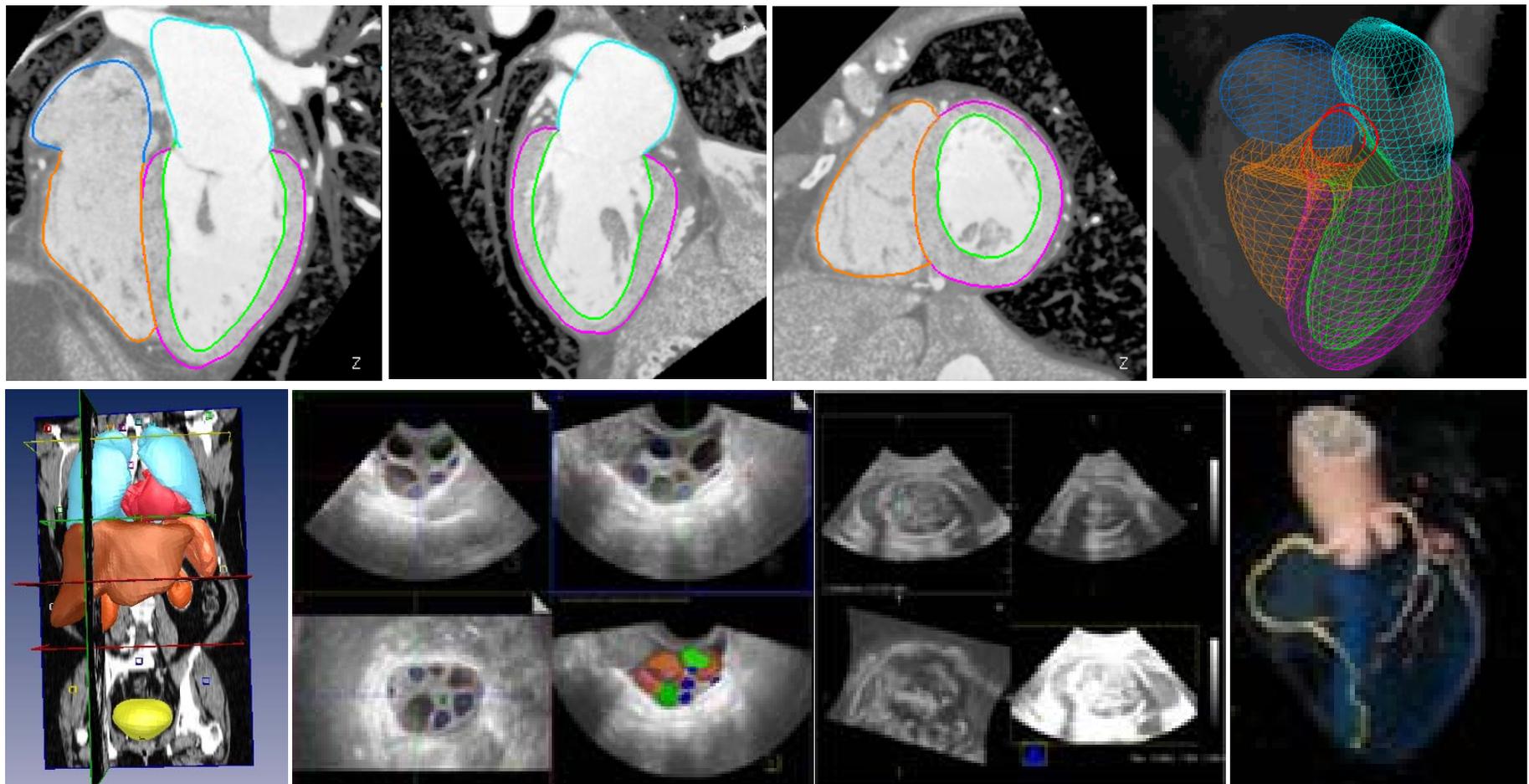


PBT + MSL

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- PBT + MSL has been widely applied to many different applications in 2D, 3D, 4D across various imaging modalities, and has been proven a very robust and efficient way for object/landmark detection



Device Tracking by Robust Detection

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- **Data has large variation – patient, clinical setting, radiation, etc.**
 - **Variation of the ground truth of each device is limited**
 - **We use large training data to cover large data variation**
- **Representative work**
 - **Needle tracking: Wang et al. ISBI 2010**
 - **Guidewire tracking: Wang et al. CVPR 2009**
 - **Catheter tracking: Wu et al. CVPR 2011**
 - **Marker/ wire tracking: Lu et al. CVPR 2011**
 - **Combinations: Wang et al. MICCAI 2011**

Needle tracking

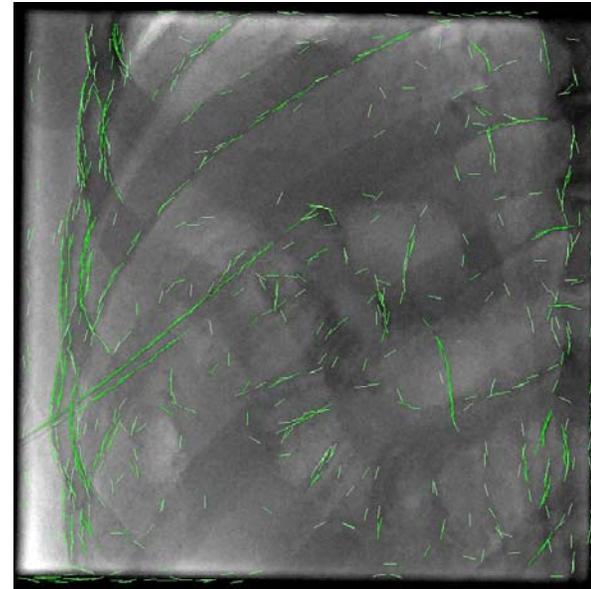
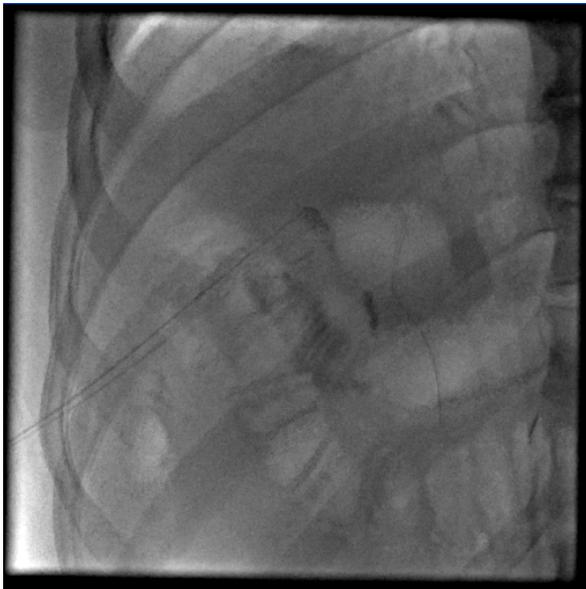
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- Learning-based Needle segment detection

- Advantages:

- Can detect relatively weak needle segments
 - Less false detections compared to filtering based methods



Needle Tracking

- **Needle tracking: track the rigid motion of a needle that is caused by breathing motions**
- **Needle tracking is to maximize the posterior probability of a tracked needle**

$$P(\Gamma_t | \mathbf{Z}_t) \propto P(\Gamma_t) P(\mathbf{Z}_t | \Gamma_t(\mathbf{u})) \quad \hat{\Gamma}_t = \underset{\Gamma_t}{\operatorname{argmax}} P(\Gamma_t | \mathbf{Z}_t).$$

$\Gamma_t(\mathbf{u}) = T(\Gamma_{t-1}, \mathbf{u})$: a needle shape at the t -th frame, which is transformed from a previous frame

\mathbf{Z}_t : image observation at the t -th frame

- Prior model: to impose a smooth movement constraint

$$P(\Gamma_t) = \frac{1}{\sqrt{2\pi}\sigma_\Gamma} \exp\left(-\frac{|D(\Gamma_t, \Gamma_{t-1})|^2}{2\sigma_\Gamma^2}\right)$$

- Measurement model $P(\mathbf{Z}_t | \Gamma_t(\mathbf{u}))$: to integral the detection scores along the needle shape $P(\mathbf{Z}_t | \Gamma_t(\mathbf{u})) = \frac{1}{|\Gamma_t(\mathbf{u})|} \sum_{\mathbf{x}_i \in \Gamma_t(\mathbf{u})} P(\mathbf{Z}_t | \mathbf{x}_i)$

Coarse-to-Fine Tracking by Kernel Smoothing

- **Kernel smoothing of measurements: to obtain a smooth density surface given a number of features (detected segments \mathbf{x}_j^s)**

$$\begin{aligned}
 P(\mathbf{Z}_t | \mathbf{x}_i) &= \sum_j P(\mathbf{Z}_t | \mathbf{x}_j^s, \mathbf{x}_i) P(\mathbf{x}_j^s | \mathbf{x}_i) \\
 &= \sum_j P(\mathbf{Z}_t | \mathbf{x}_j^s) G_\sigma(\mathbf{x}_j^s, \mathbf{x}_i)
 \end{aligned}$$

- **A Gaussian kernel is used**

$$P(\mathbf{x}_j^s | \mathbf{x}_i) = G_\sigma(\mathbf{x}_j^s, \mathbf{x}_i)$$

- **Coarse-to-Fine tracking: adaptively change kernel size σ . in the Gaussian kernel, according to the searching step at each iteration**

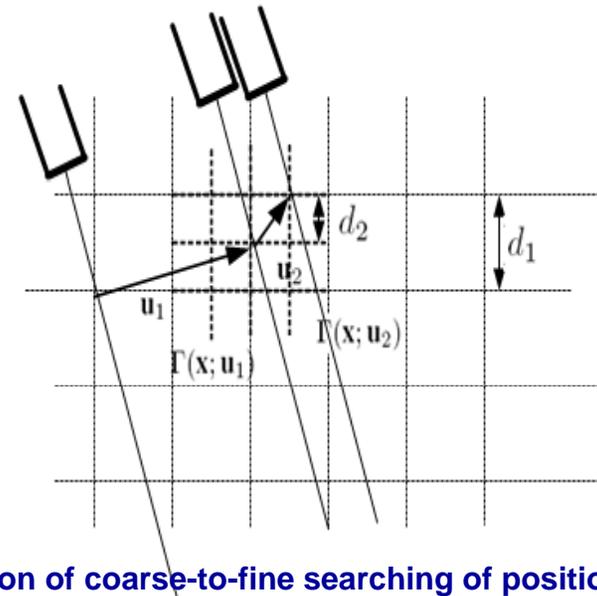
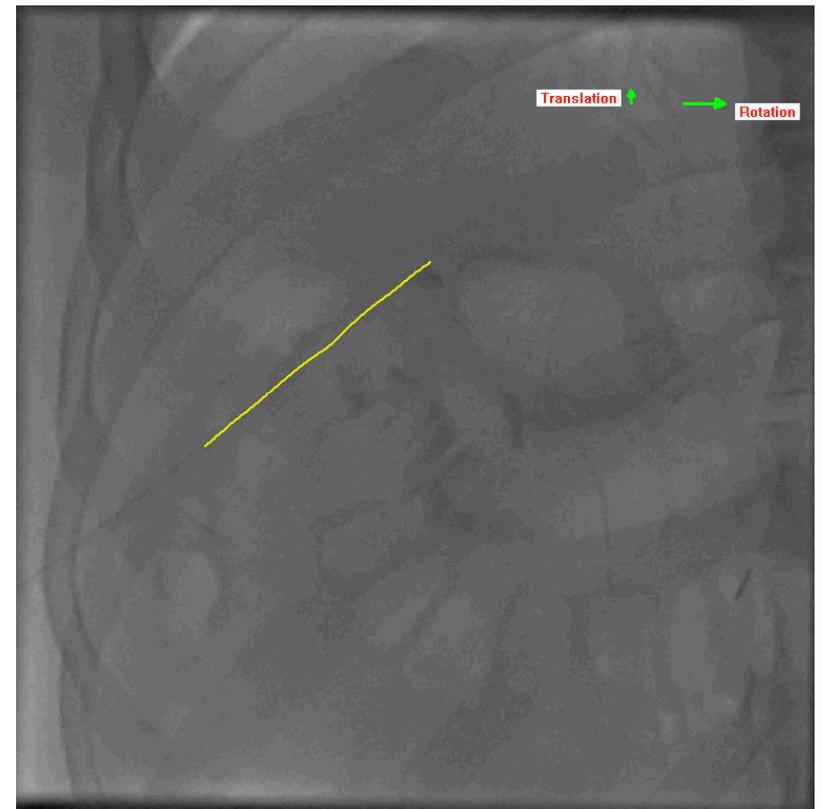


Illustration of coarse-to-fine searching of positions

Robustness to Initialization on Tracking

- To study the robustness against various initializations on the tracking, users are asked to randomly initialize a part of the needle for tracking;
- Tracking with partial initialization is slightly worse, but the accuracy is comparable to the tracking with full initializations



Quantitative evaluation on clinical data

Initialization	frame tracking rate	Pixel error		
		median	mean	std
Full	96.3%	1.31	2.96	5.16
Partial	94.6%	1.83	3.07	4.71

- Full: 10 sequences 1312 frames
- Partial: 20 times initialization – 200 tracking results

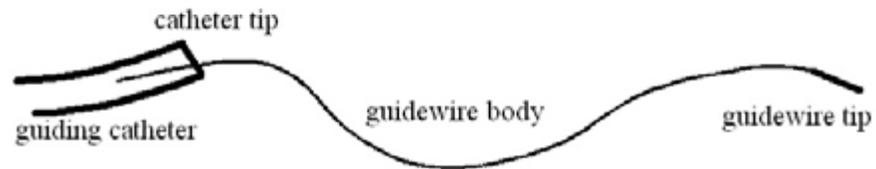
Guidewire tracking

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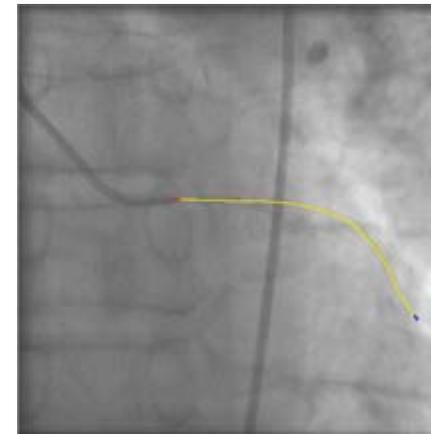
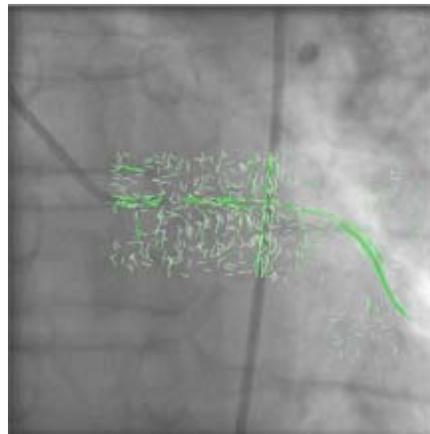
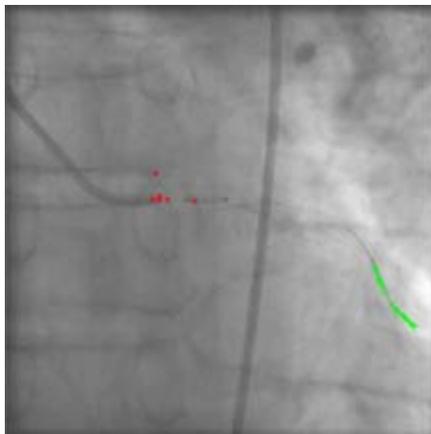


- **Guidewire - A non-rigid deformable needle**

- **Model –**



- **Detection –**



Formulation of the tracking problem

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- The same Bayesian Inference Framework as Guidewire Tracking

$$P(\Gamma_t(\mathbf{x})|\mathbf{Z}_t) \propto P(\Gamma_t(\mathbf{x}))P(\mathbf{Z}_t|\Gamma_t(\mathbf{x}))$$

- For the guidewire model, we have three different components

$$P(\mathbf{Z}_t|\Gamma_t(\mathbf{x})) = \sum_{\mathbf{x}_i} P(\mathbf{Z}_t|\mathbf{x}_i)P(\mathbf{x}_i|\Gamma_t(\mathbf{x})),$$

- $P(\mathbf{Z}_t|\mathbf{x}_i)$ is the measurement at individual point , $P(\mathbf{x}_i|\Gamma_t(\mathbf{x}))$ is the weights

$$P(\mathbf{Z}_t|\Gamma_t(\mathbf{x})) = \omega_1 P(\mathbf{Z}_t|\mathbf{x}_1) + \omega_N P(\mathbf{Z}_t|\mathbf{x}_N) + \frac{1 - \omega_1 - \omega_N}{N - 2} \sum_{i=2}^{N-1} P(\mathbf{Z}_t|\mathbf{x}_i).$$

- Fusion of multiple measurements
 - Detection measurements + Appearance measurements

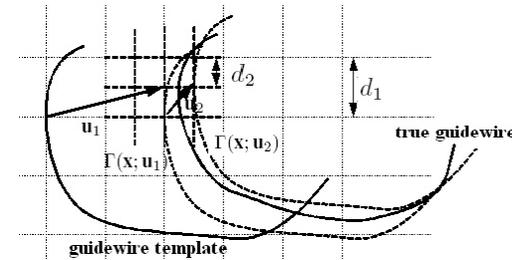
$$P(\mathbf{Z}_t|\mathbf{x}_i) = P^d(\mathbf{Z}_t|\mathbf{x}_i)P_d + P^a(\mathbf{Z}_t|\mathbf{x}_i)P_a$$

Multi-resolution Guidewire Tracking

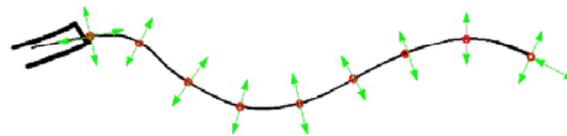
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- Kernel –based measurement smoothing



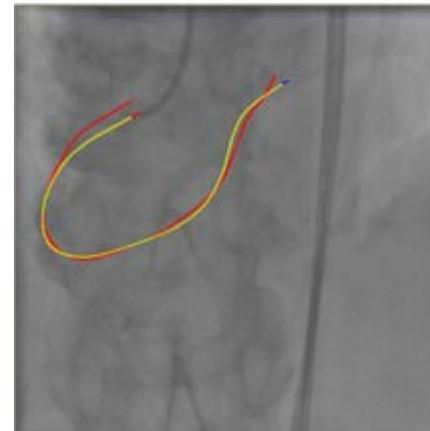
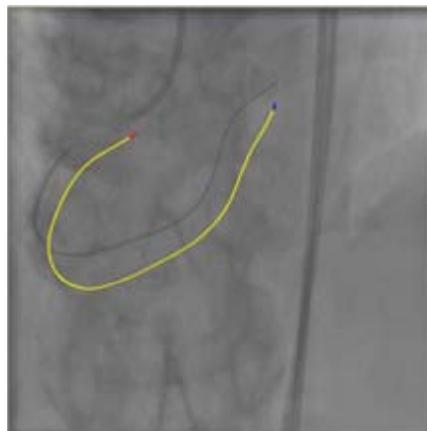
- Rigid tracking



- Non-rigid tracking

$$E(\mathbf{u}_x) = P(\Gamma_t(\mathbf{x}; \mathbf{u}_x) | Z_t) + \alpha \int \left| \frac{d\Gamma_t(\mathbf{x}; \mathbf{u}_x)}{ds} \right|^2 d\mathbf{x} + \beta \int \left| \frac{d^2\Gamma_t(\mathbf{x}; \mathbf{u}_x)}{ds^2} \right|^2 d\mathbf{x}.$$

- Result

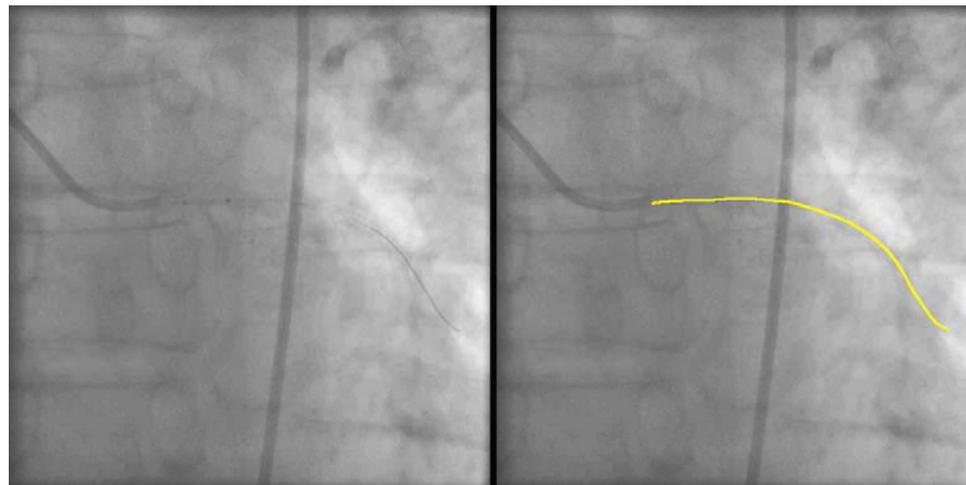


Guidewire tracking evaluation

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- Evaluated on 47 sequences with thousands of frames
- Trained on about 500 frames



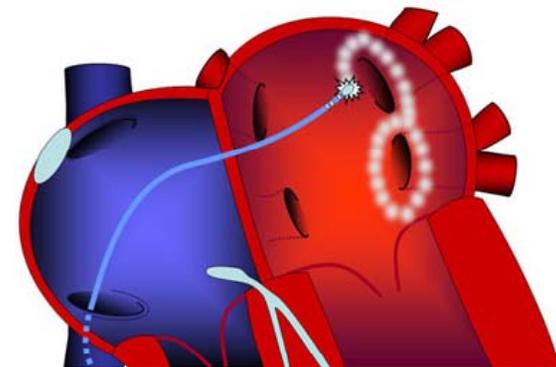
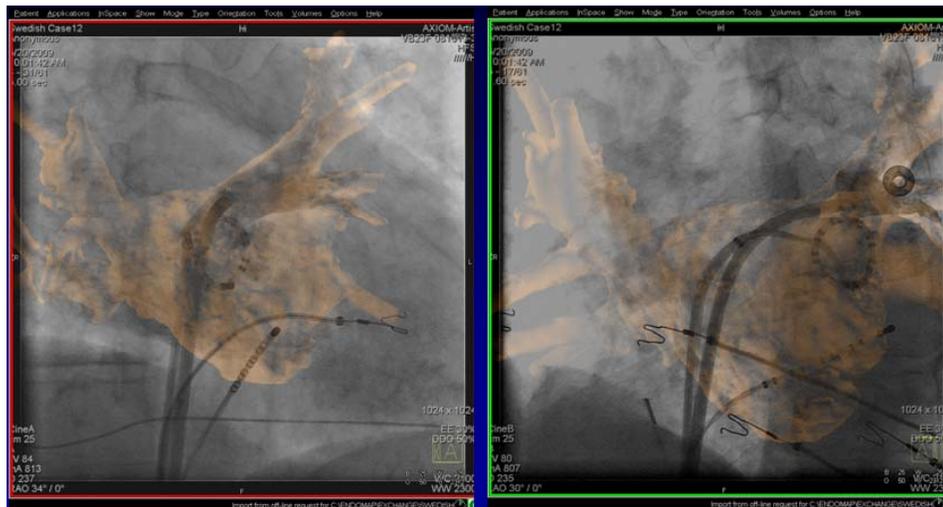
Measurements models	With combined models			With only offline learned models		
	mean	std	median	mean	std	median
Overall GW Tracking Prec. (in pixels)	1.80	3.41	0.95	7.53	27.37	1.05
GW Body Tracking Prec. (in pixels)	1.70	2.96	0.95	1.79	4.02	0.97
GW Tip Tracking Prec. (in pixels)	5.45	8.21	3.69	9.06	15.43	3.79
Cath. Tip Tracking Prec. (in pixels)	11.62	12.76	7.18	68.33	76.85	35.85
GW Missing Tracking Rate	9.88%	8.43%	8.27%	11.06%	13.97%	8.55%
GW False Tracking Rate	9.62%	6.92%	7.80%	11.87%	9.74%	9.33%

Catheter tracking in EP procedures

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- Tracking different types of catheters during the EP procedures
 - Provide motion compensation guidance
 - Provide ablation coordinates related to the 3D LA model

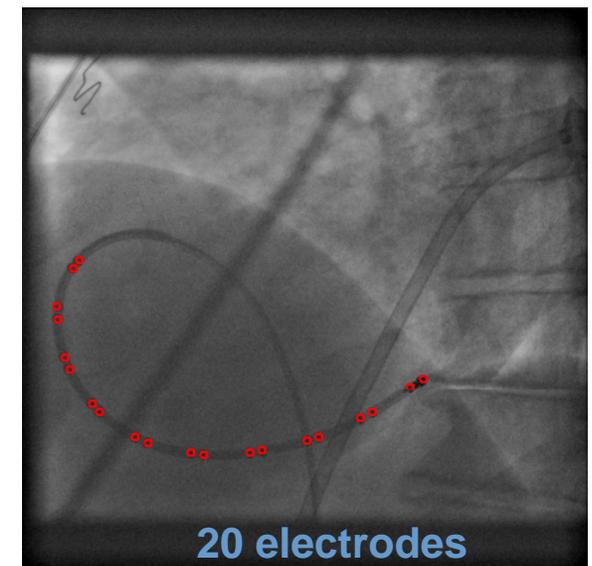
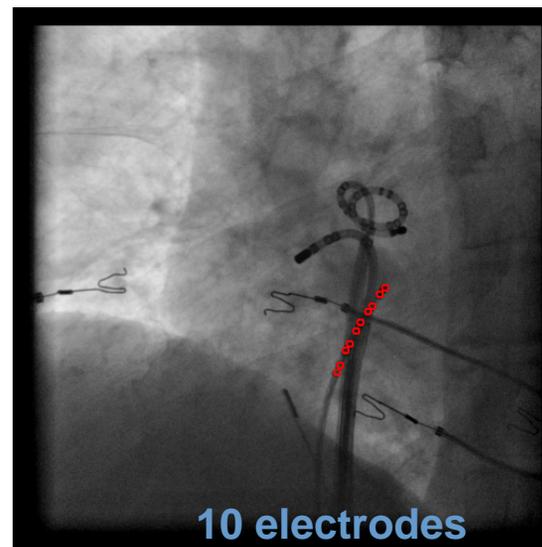
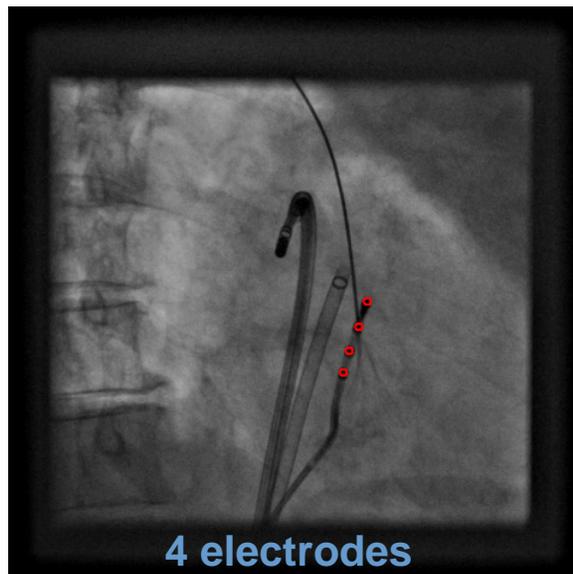


Catheter tracking

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- Model the catheter as a vector of electrodes
 - For motion compensation, correspondences between frames are important
 - If a point at the more proximal point is needed, we can infer it using geodesic distance



Hypothesis Fusion

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- Detection: Large-scaled learned electrodes, catheter tip, and catheter body classifiers
- Hypothesis fusion:
 - Type I : Assume at least one electrode is detected correctly, match the detected electrode candidates at frame t to all electrodes at frame $t-1$ and generate hypotheses
 - Type II: Assume that the tip and one of the electrodes are correctly detected and either the tip or the electrode has reliable orientation, generate hypotheses
- Bayesian framework
 - $P(Z_t|C_t) = (1 - \lambda) \cdot P(E_t^*|C_t) + \lambda \cdot P(T_o^s|C_t)$

$$\lambda = \frac{1}{1 + e^{-f(T_o^s, D(C_t))}}, f(T_o^s, D(C_t)) = \frac{\text{cov}(T_o^s, D(C_t))}{\sigma(T_o^s) \cdot \sigma(D(C_t))}$$

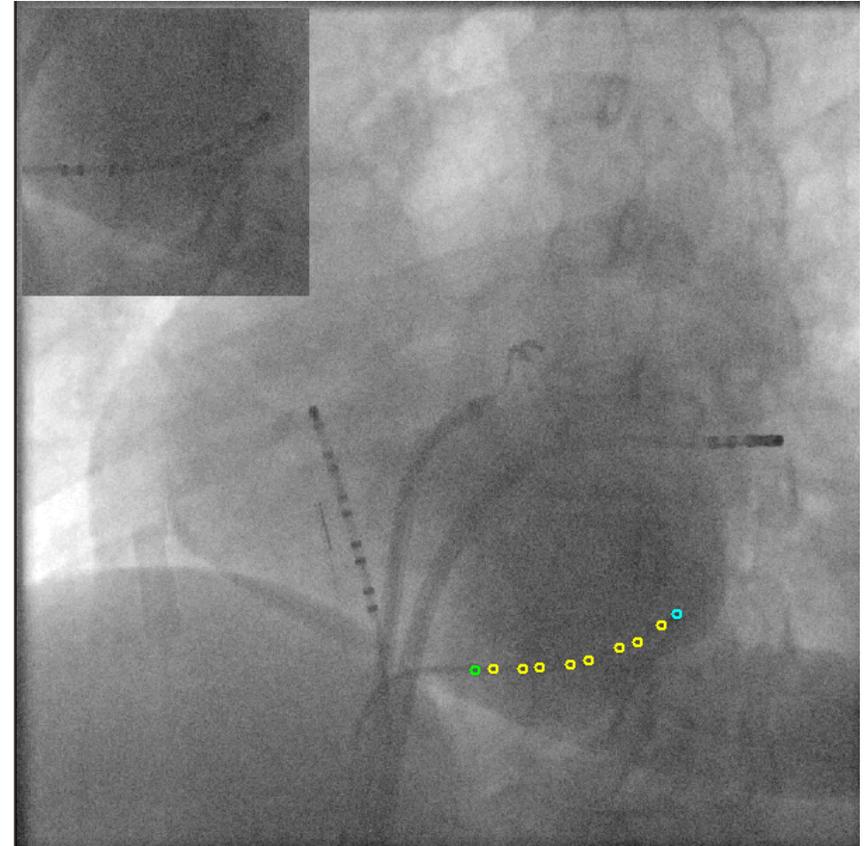
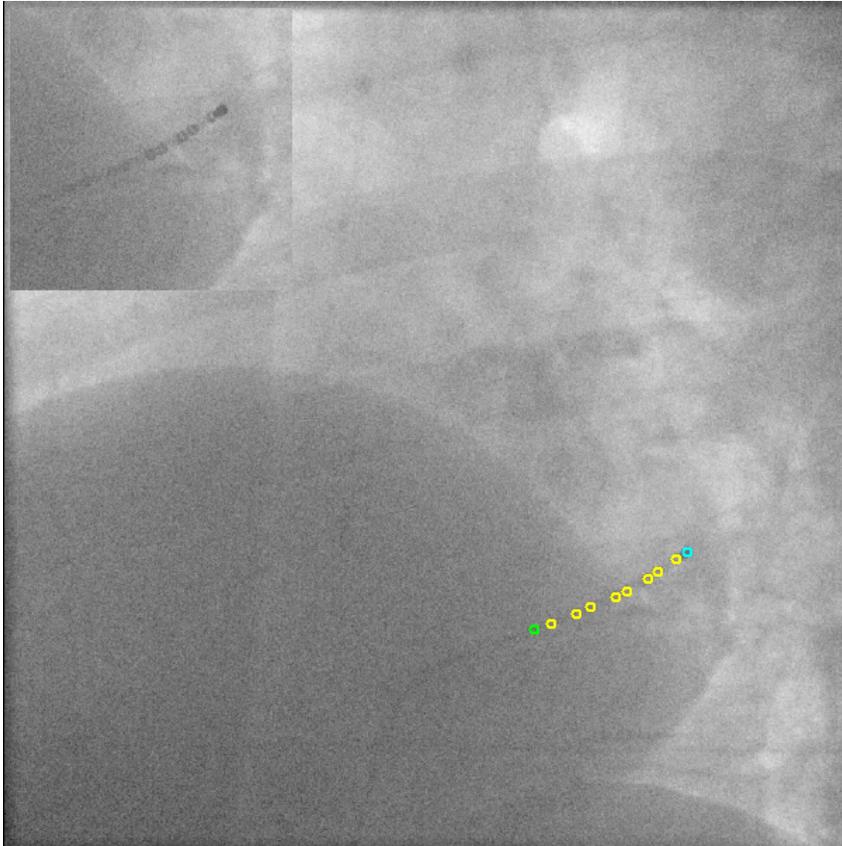
$$P(E_t^*|C_t) = \nu_1 P(E_t^*|e_t^1) + \nu_K P(E_t^*|e_t^K) + \frac{1 - \nu_1 - \nu_K}{K - 2} \sum_{i=2}^{K-1} P(E_t^*|e_t^i)$$

- Online model update

EP Catheters Tracking

Highly noisy data

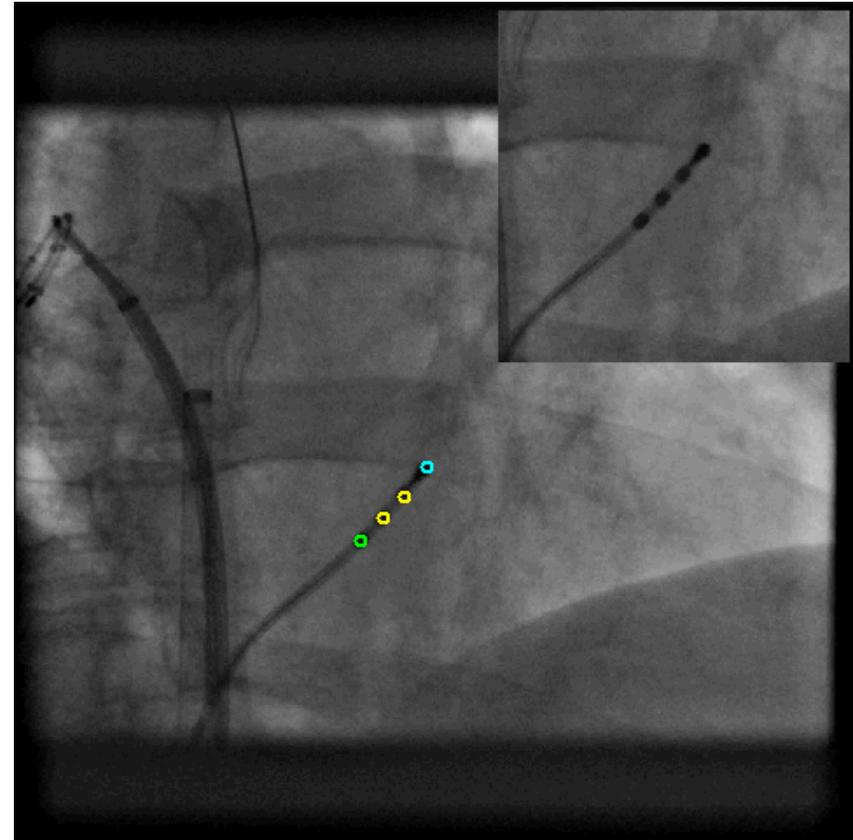
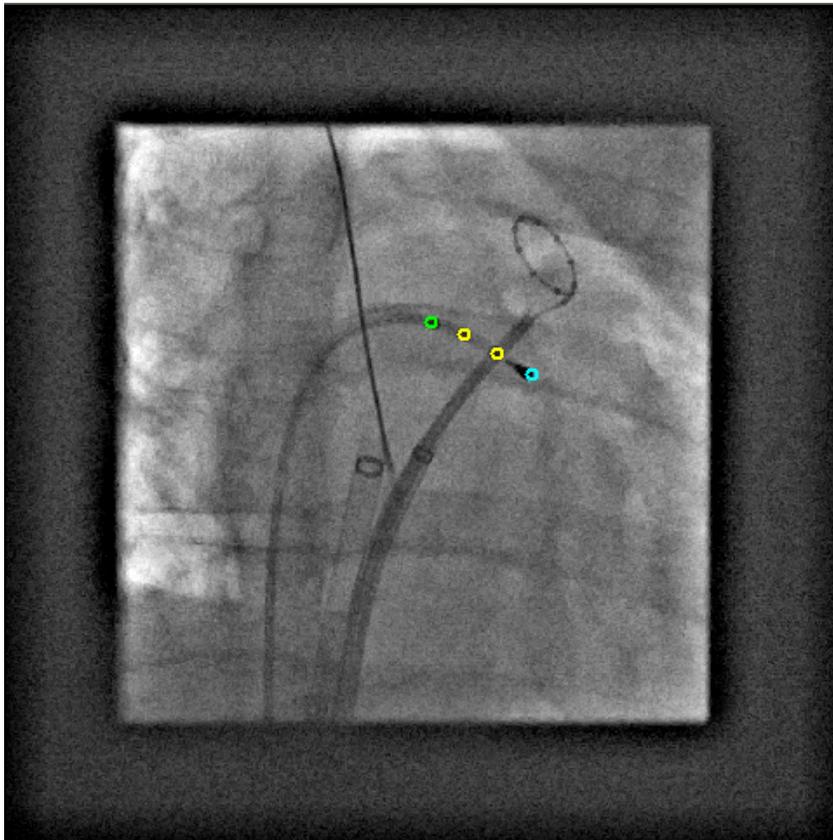
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EP Catheters Tracking

Rapid motion

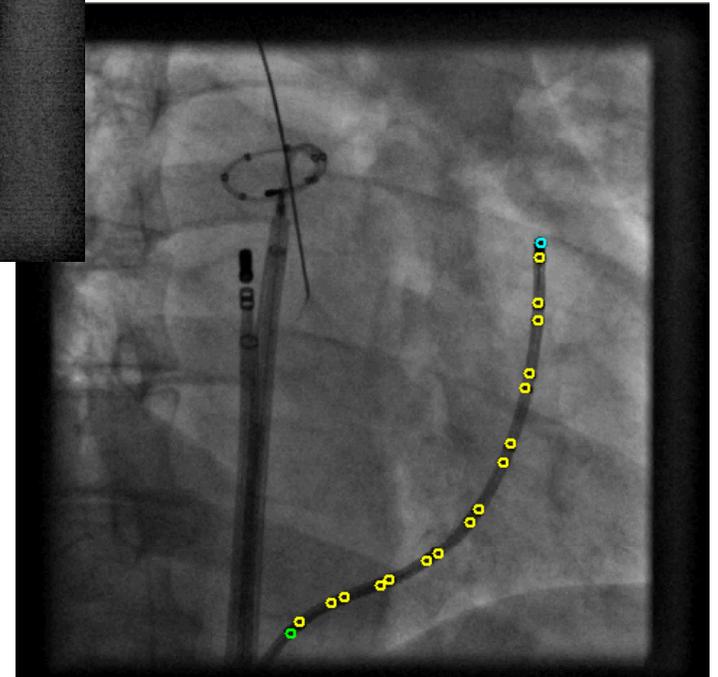
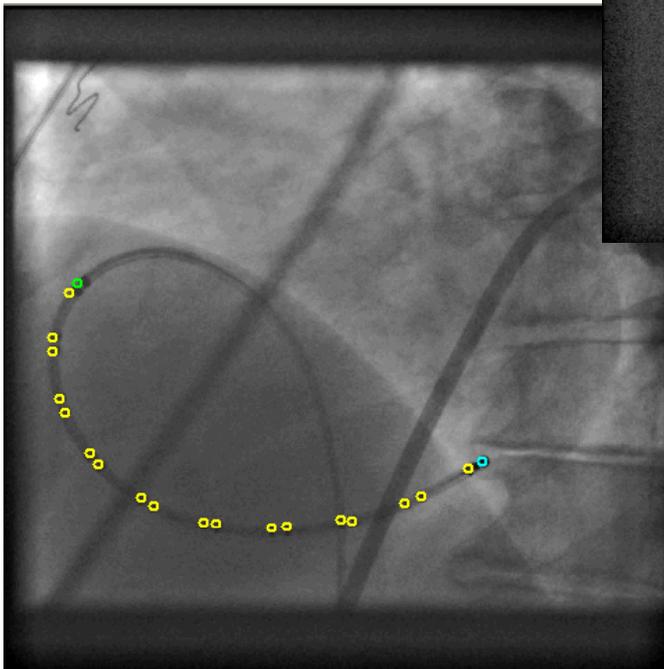
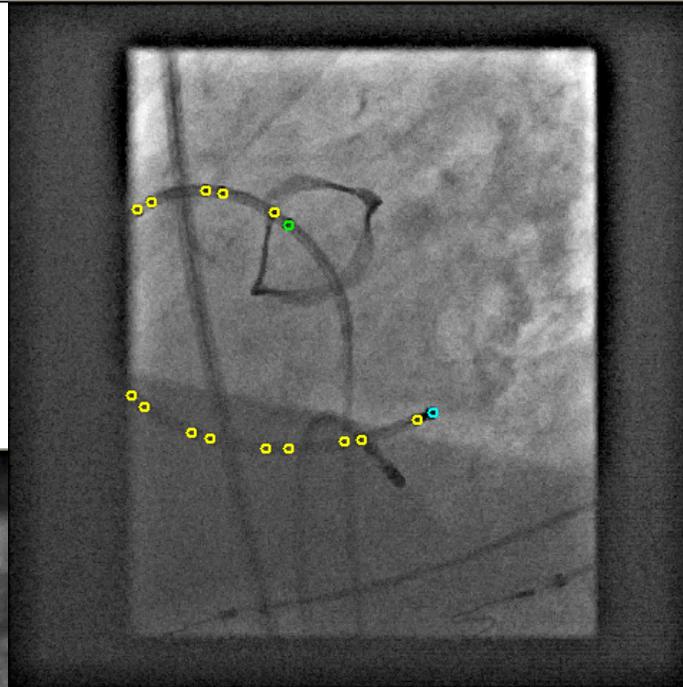
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EP Catheters Tracking

Non-rigid deformation

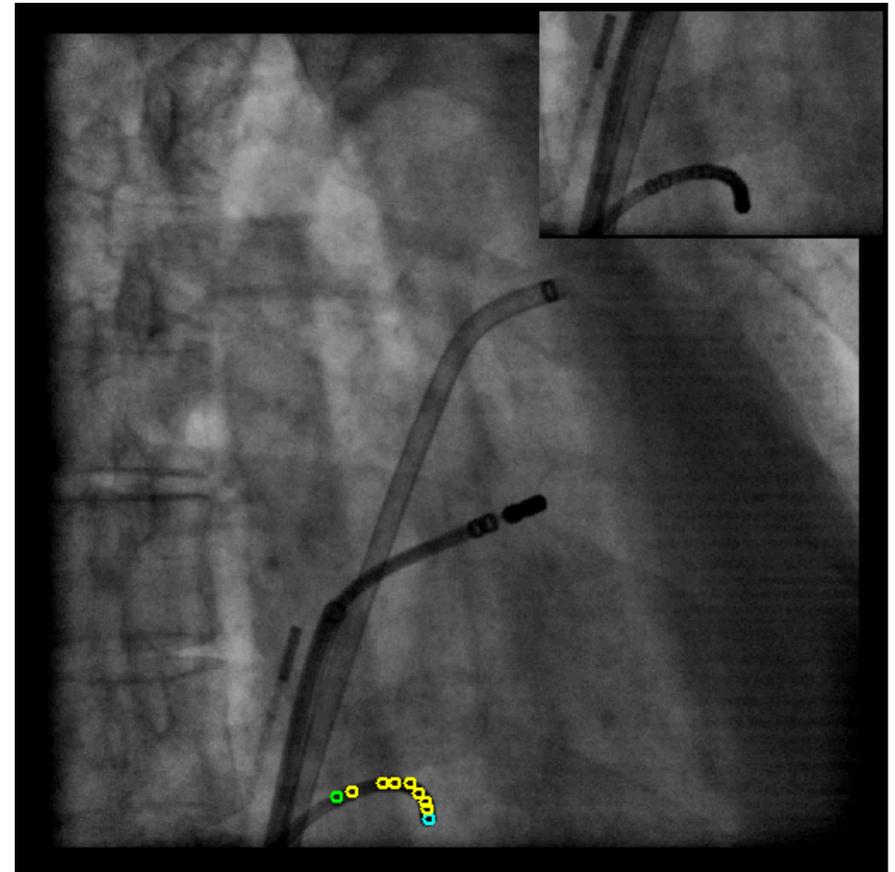
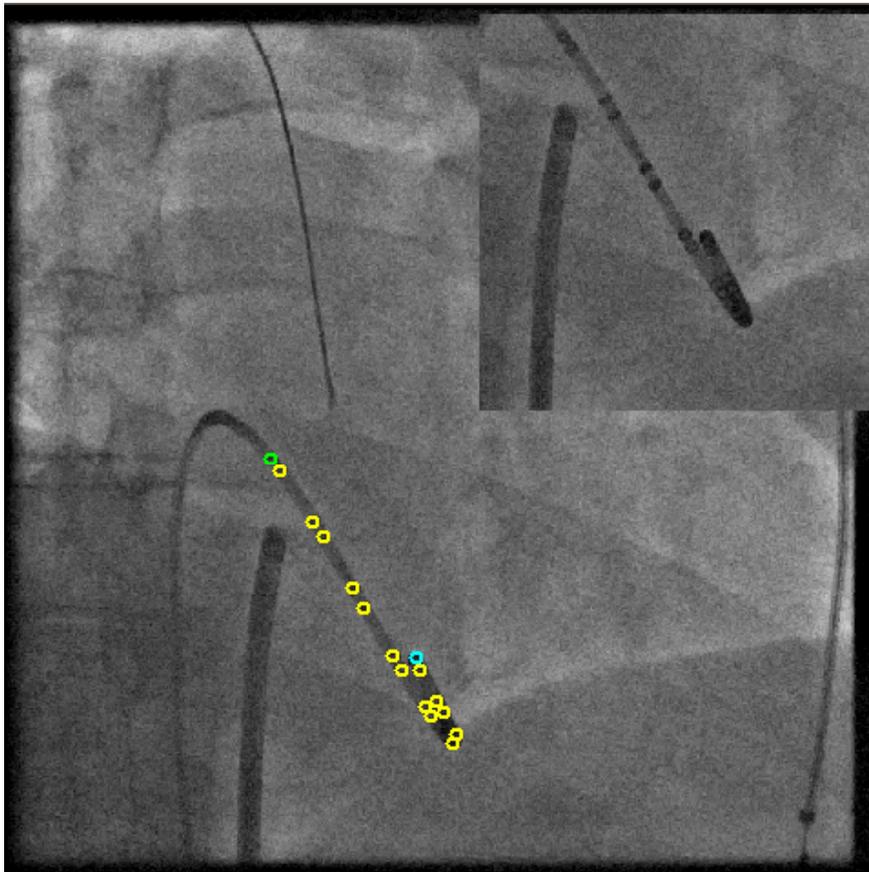
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EP Catheters Tracking

Severe foreshortening

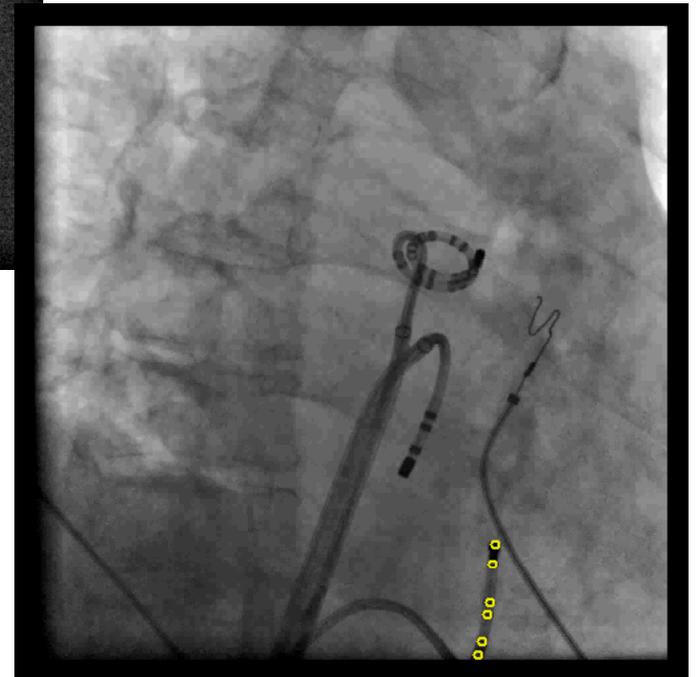
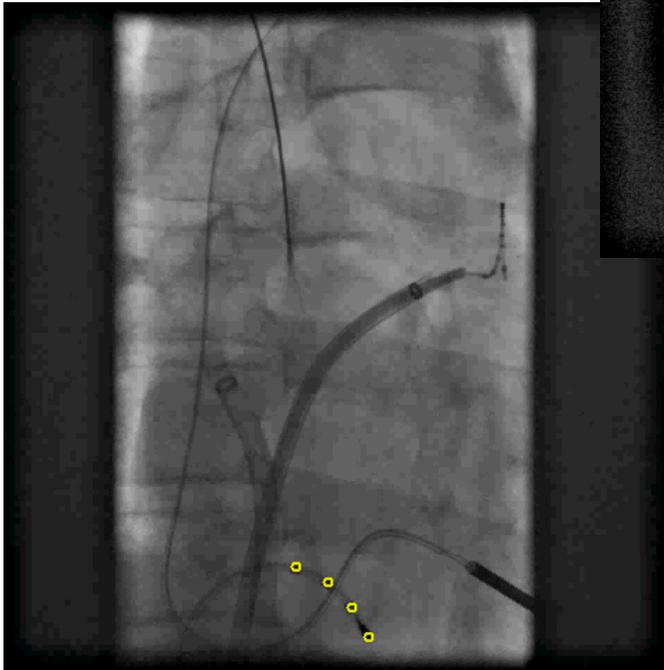
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EP Catheters Tracking

Moving out of ROI

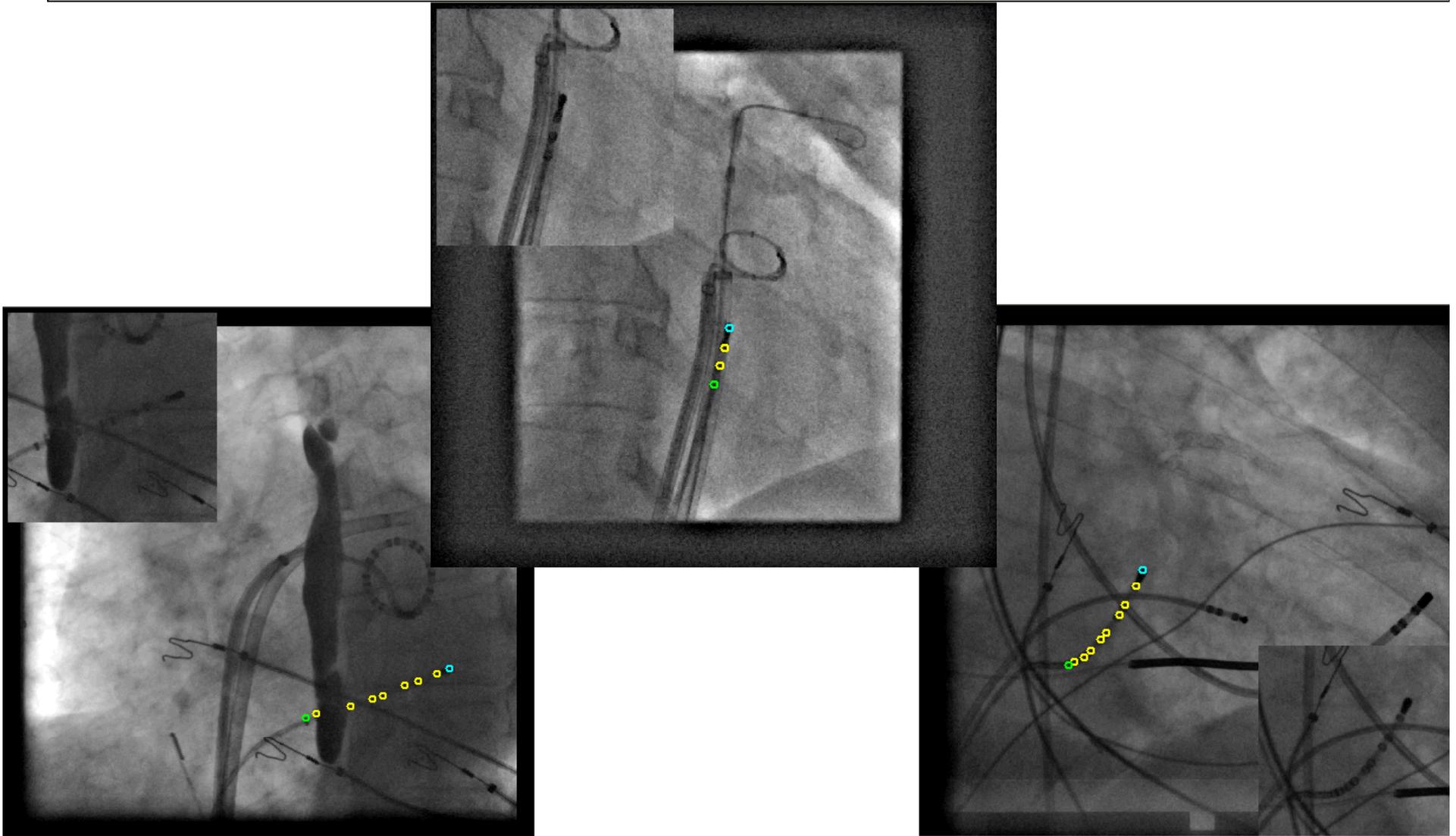
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EP Catheters Tracking

Partially occlusion, overlapping with cluttered background

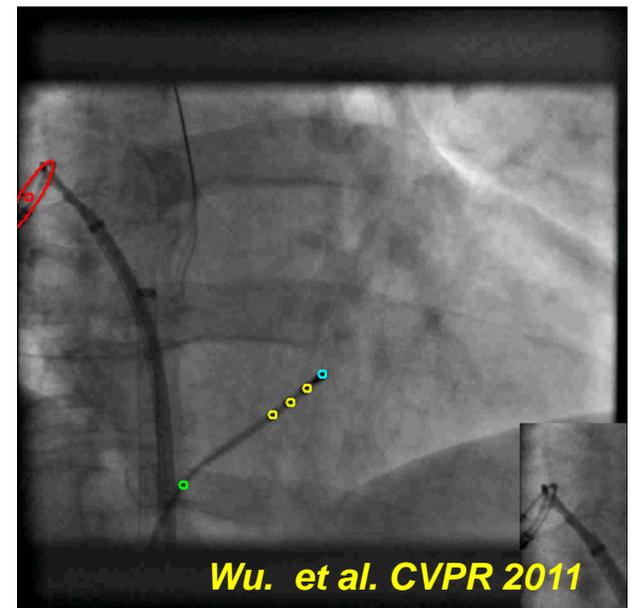
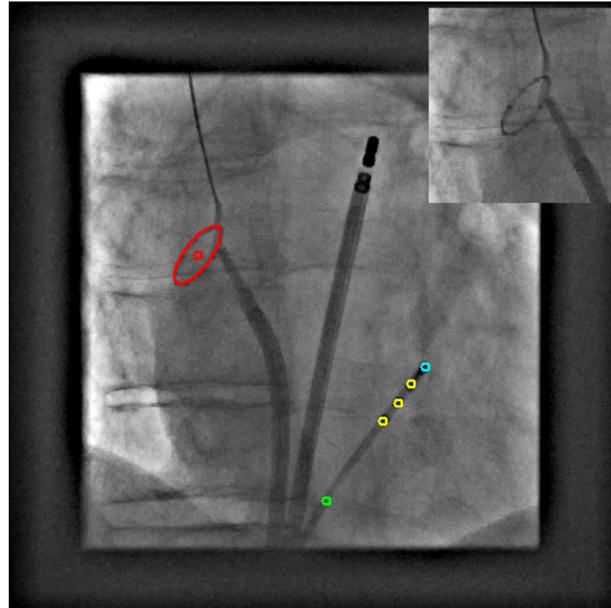
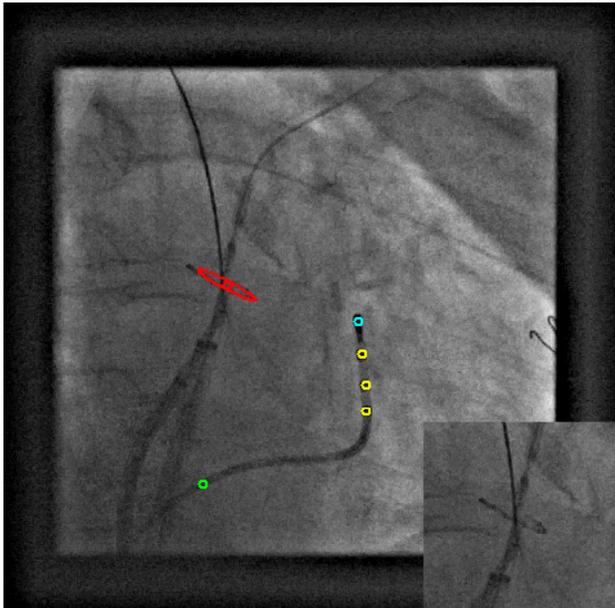
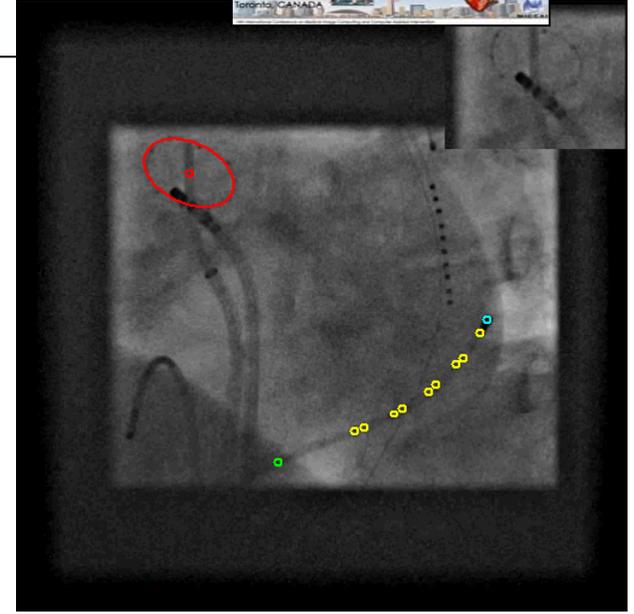
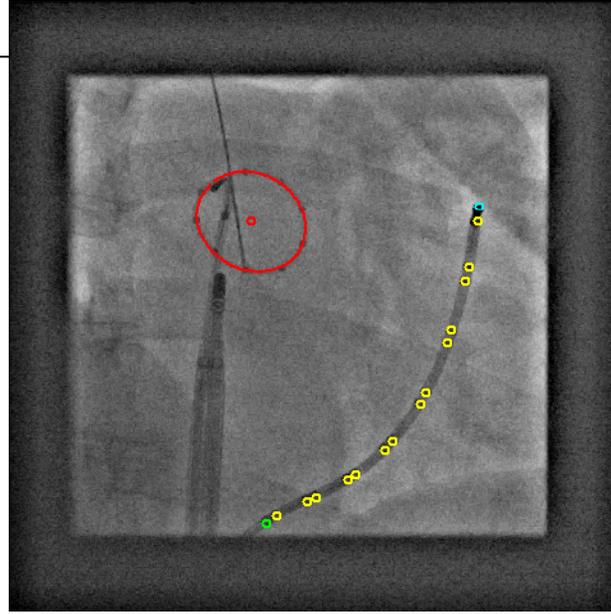
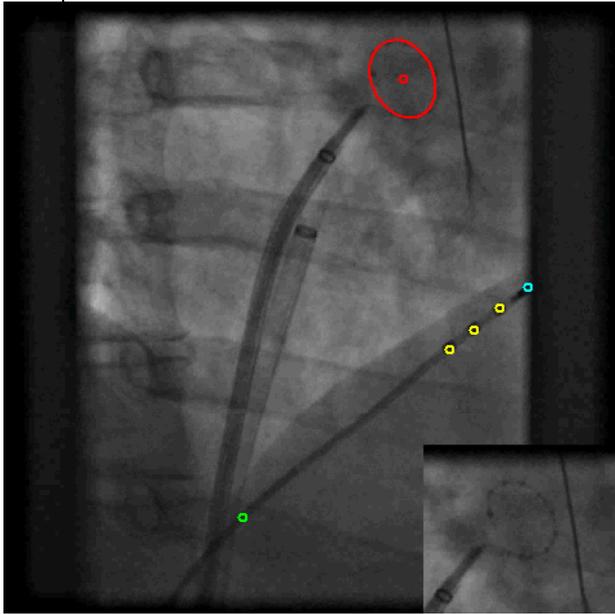
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Multiple catheters tracking

2 catheters

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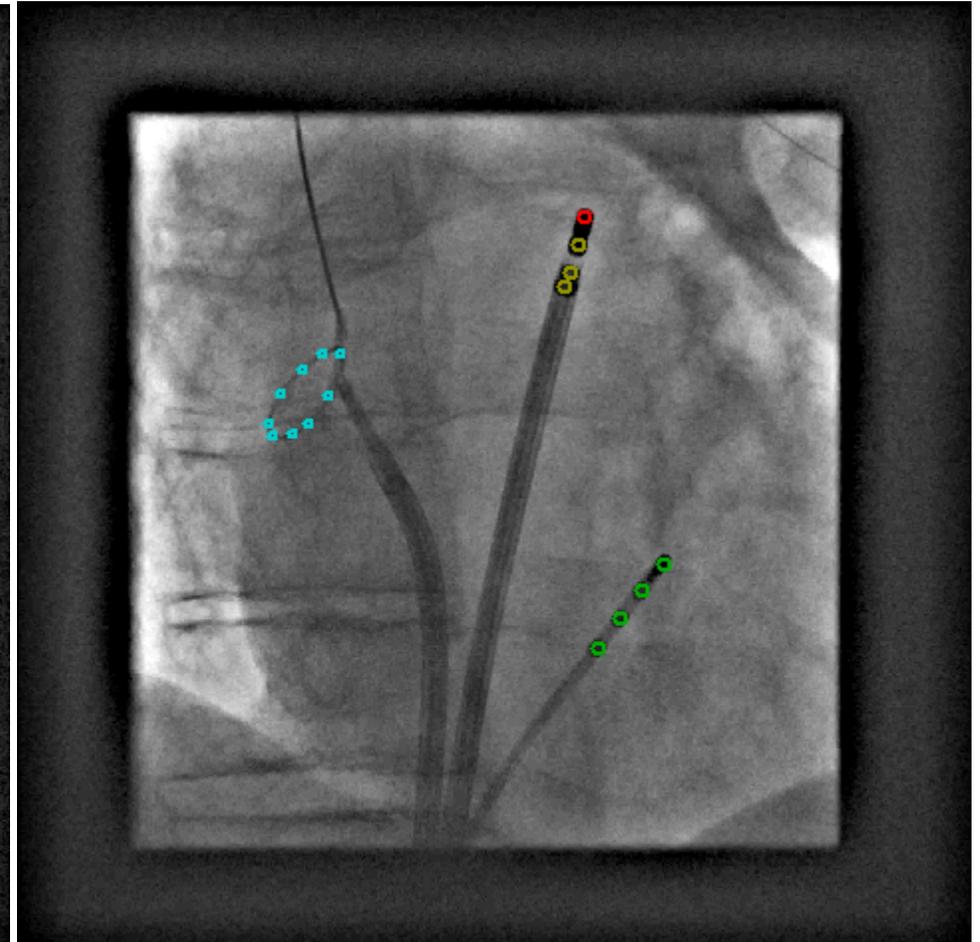
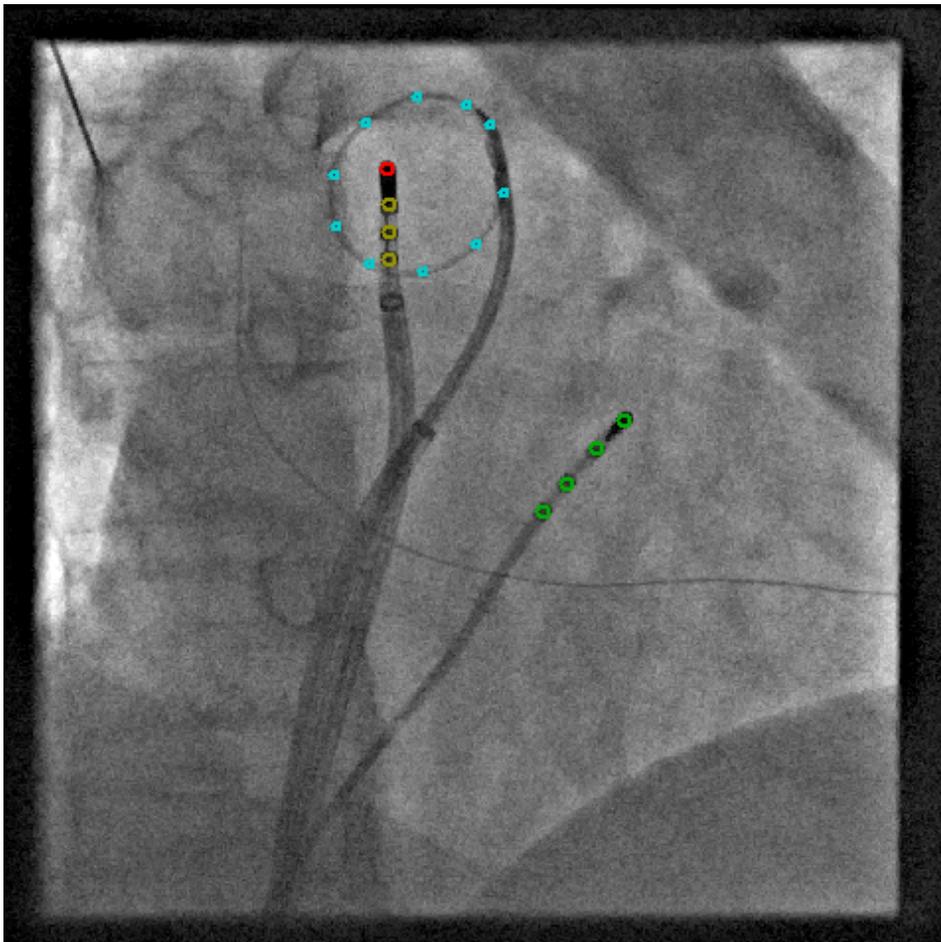


Wu. et al. CVPR 2011

Multiple catheters tracking

3 catheters

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Quantitative Evaluation

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- CS catheter tracking evaluation: 1073 evaluated sequences with more than ten thousand frames. All errors are in mm.

Mean	Median	P85	P90	P95	P98
0.8	0.5	0.7	0.8	1.0	1.9

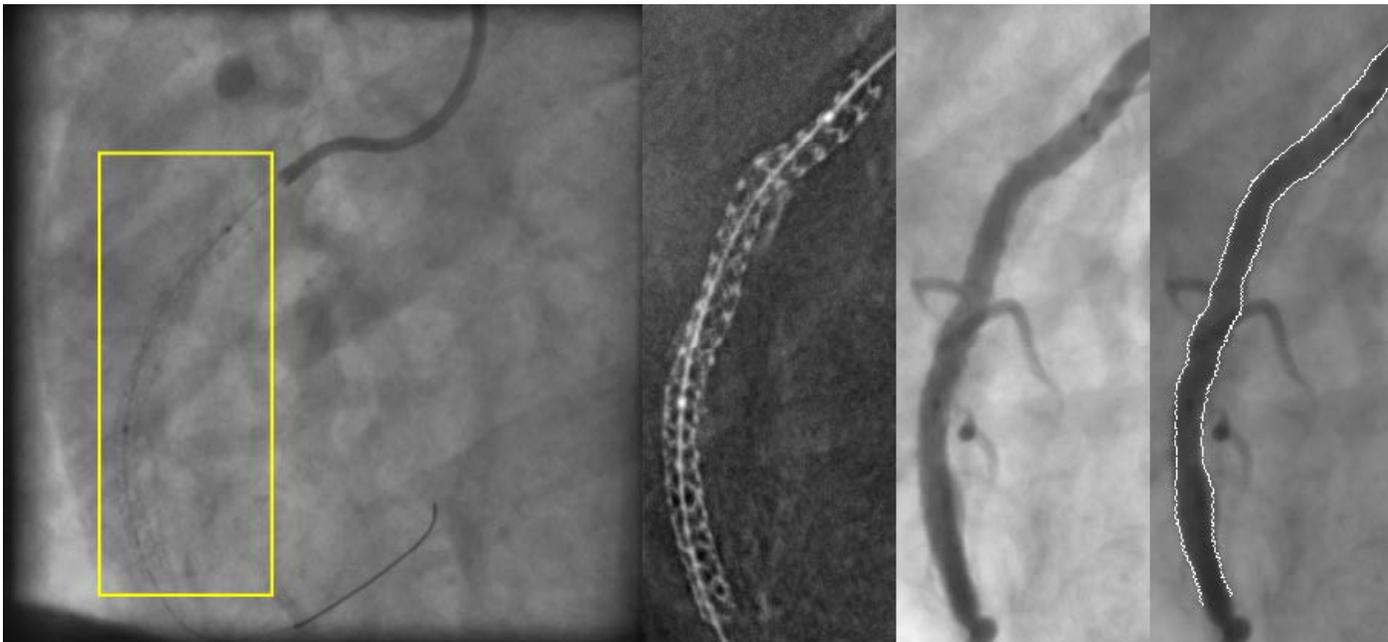
- Lasso and ablation catheters are with similar performance
- Single catheter tracking speed: ~20 fps (CPU), ~35 fps (CPU+GPU)

Marker & Wire detection/tracking

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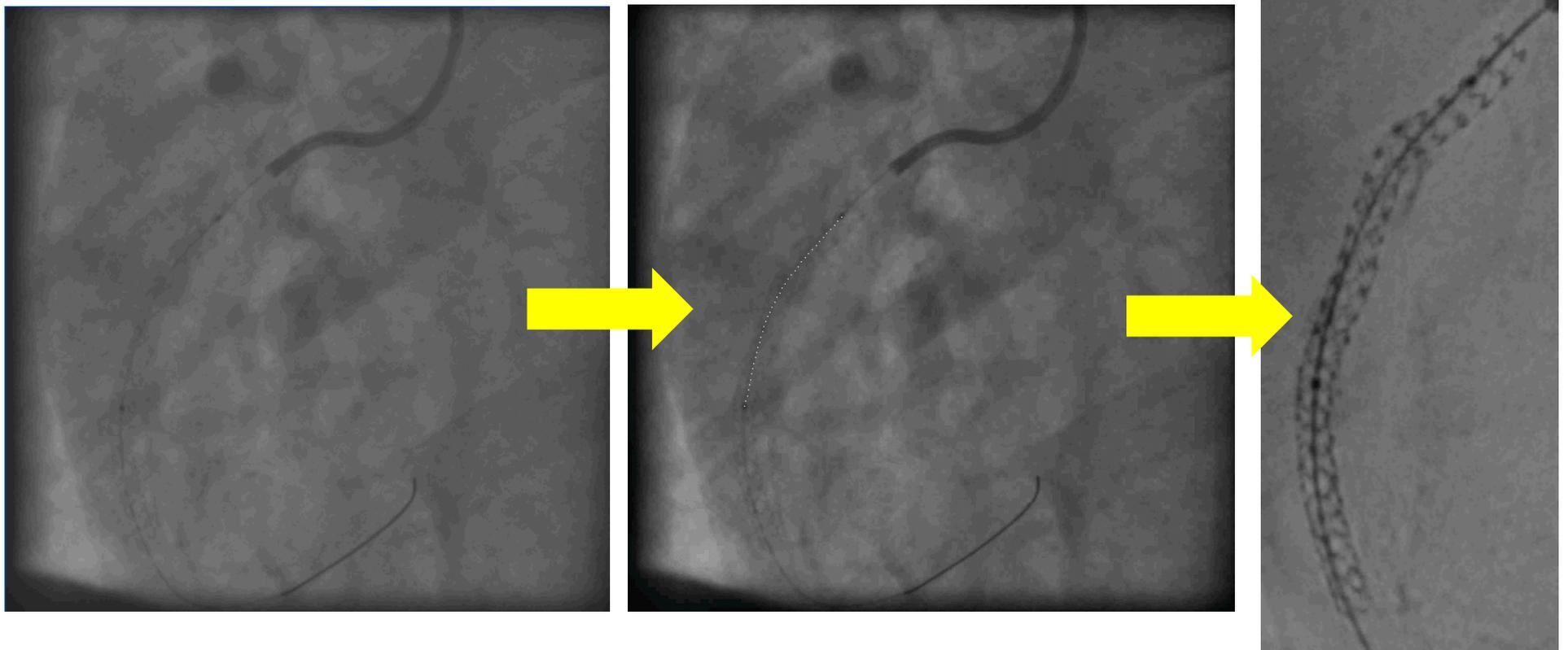


- Stent visualization via continuous marker and wire detection/tracking



Detect & Track the marker and wire for stent enhancement

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Model the wire + markers together

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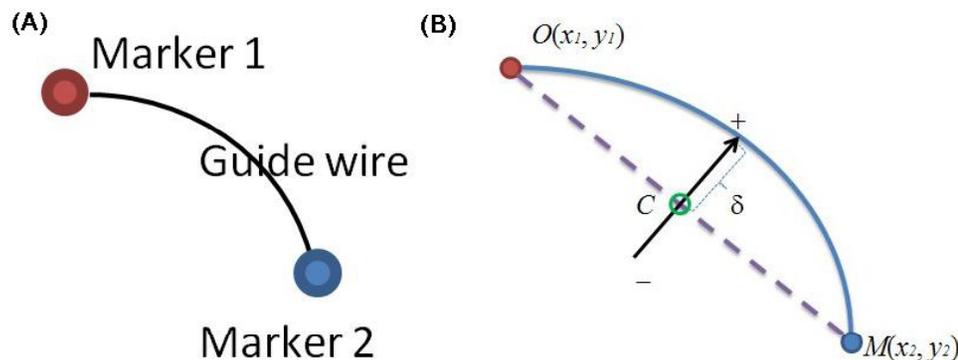
- Model the target pattern as two markers with a parametric wire in-between

$$\chi(O, M, \delta),$$

where $O = (x_1, y_1)$ and $M = (x_2, y_2)$ are the locations of the two balloon markers, where $x_1 \leq x_2$, and $y_1 \leq y_2$ if $x_1 = x_2$. δ is defined as the displacement along the normal direction from the center $C = (O+M)/2$ to the guide wire.

- Calculate the final probability in a Bayesian formulation:

$$P(O, M, \delta | I) = P(O, M | I) P(\delta | O, M, I)$$



- wire is the only feature differentiate TP from FP
- fusion to improve detection rate
- efficient search with little overhead
- obtained guide wire automatically

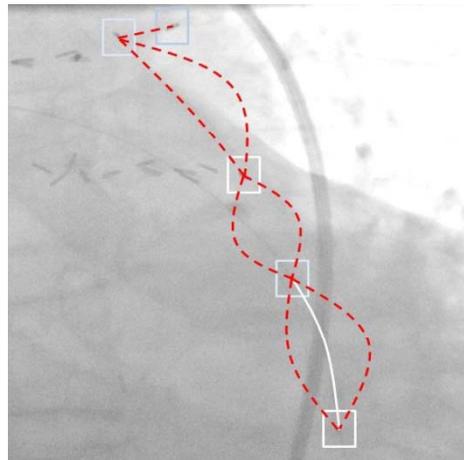
Training & Inference

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- Training :

- Boxes: marker detector responses
- White line: Positive
- Red lines: Negatives



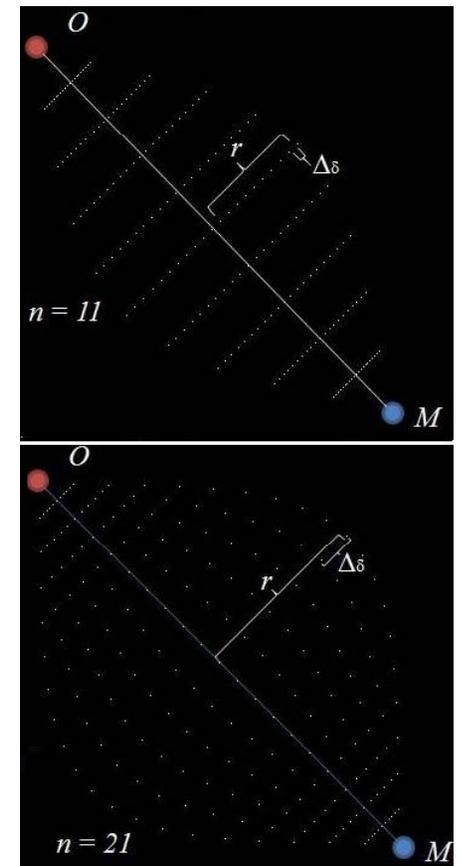
- **Marker Detection**

➤ Marker detection, $P(O, M|I)$, is formulated as into a typical object detection framework to solve a two-class (object vs. background) classification problem.

- **Guidewire Detection**

- Model the guidewire as a 2D cubic spline curve with 3 control points.
- Discretize the hypothesis space of δ by a ratio defined by $\|O-M\|_{L_2}$
- Hypothesis space of δ becomes:

$$H_{\delta} = \{ -r, -r + \Delta_{\delta}, \dots, 0, \dots, r - \Delta_{\delta}, r \}, \text{ where } r = 0.36 \times \|O-M\|_{L_2}$$



Lu. et al. CVPR 2011

Evaluation

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	Rank-1		Mean	Std	Median		Mean	Std	Median
Marker only	83%	Marker only	15.1	38.2	0.50	I	3.0184	10.3488	0.2556
Fusion of markers and wire	90%	Fusion of markers and wire	8.9	33.6	0.47	II	0.44	0.6375	0.231

- Evaluated on 12495 frames (273 scenes)
- 4 fold cross validation

Tracking – Similar to the previous work.

- Successful rate with tracking (temporal coherence) – 98 %
- Definition of success – no failure frame

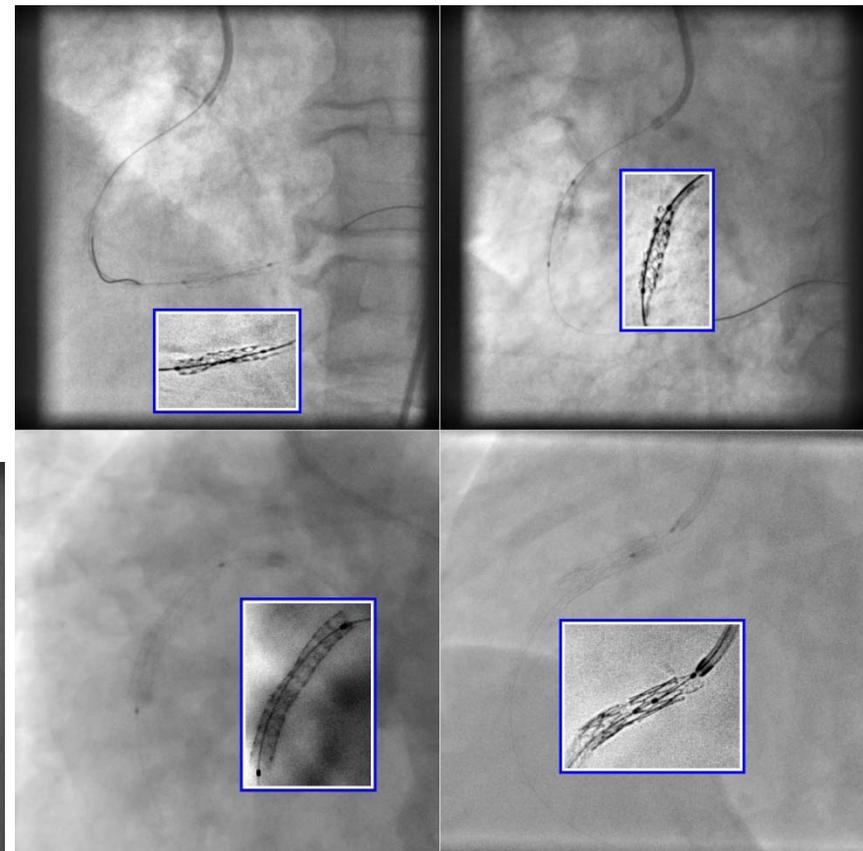


Image-based tracking technologies for registration between different imaging modality

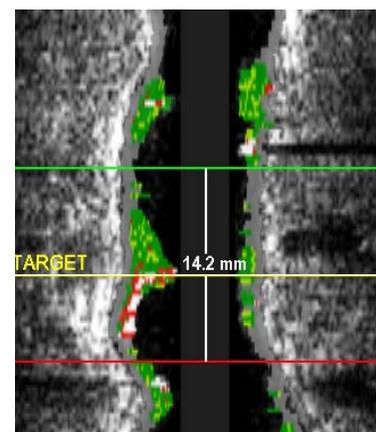
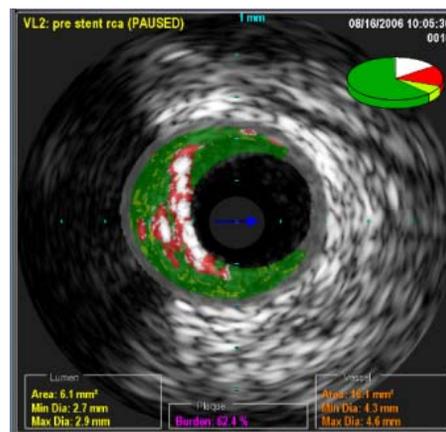
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- With robust tracking technologies, it is possible to provide registration or fusion of multiple imaging modalities, such as IVUS/Angio, OCT/Angio, Ultrasound/fluoro, etc.
- Please refer to this year's MICCAI paper: P. Wang, T. Chen, O. Ecabert, D. Comaniciu, "Image-based device tracking for the co-registration of angiography and intravascular Ultrasound images", MICCAI, 2011.
- **Goal:** To combine the Intravascular Ultrasound (IVUS) and Angiography to provide a full picture of the coronary under investigation
- **Angiography:** "Gold standard" of vessel imaging (Low spatial resolution, good orientation)
- **IVUS provides:** Information on vessel wall composition (High spatial resolution, poor orientation)



+



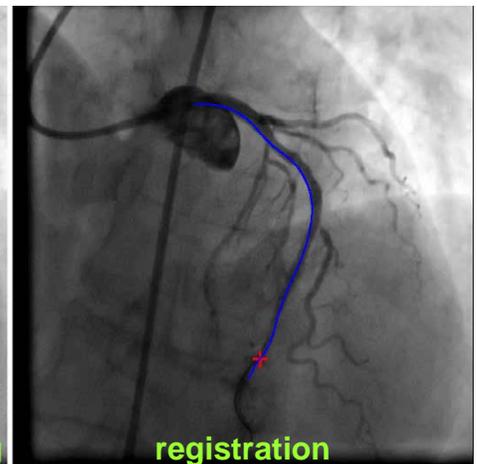
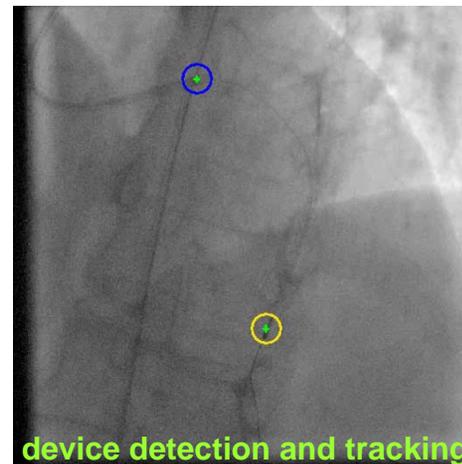
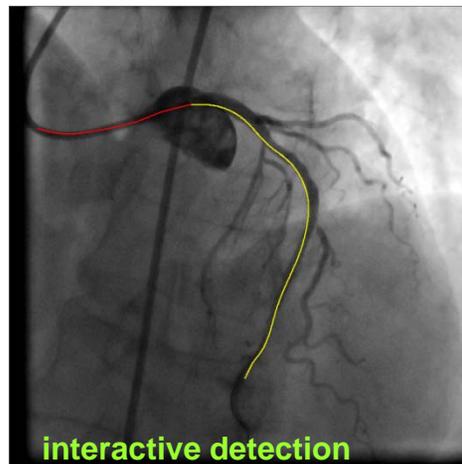
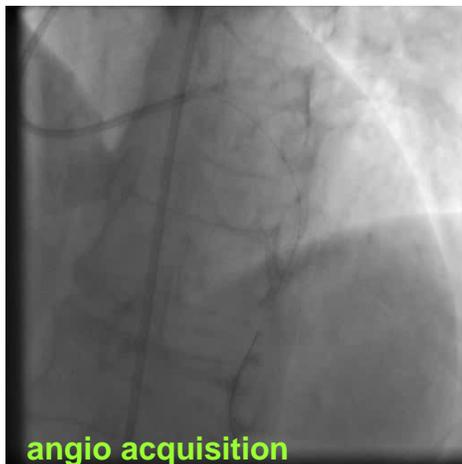
IVUS/Angio Co-registration workflow

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Workflow

- **Angio** – Interactive vessel path and guiding catheter shape detection
- **Fluoro** – An image based device detection & tracking framework; tracking through robust fusion
- **Angio/Fluoro** – Geodesic distance based registration
- **Fluoro/IVUS** – synchronized timestamps
- **Angio/IVUS** – through the ECG gated fluoro



Evaluation

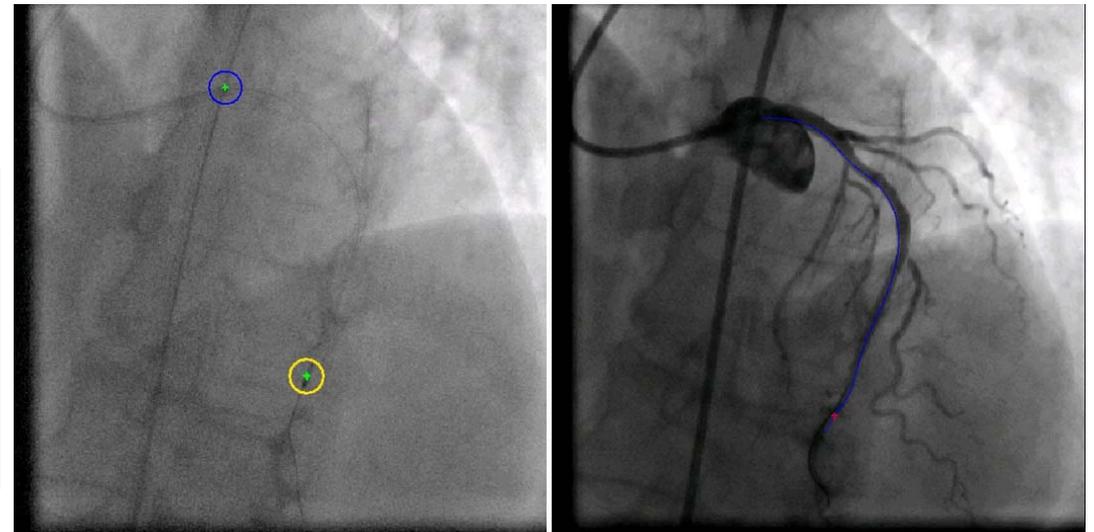
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- Performance

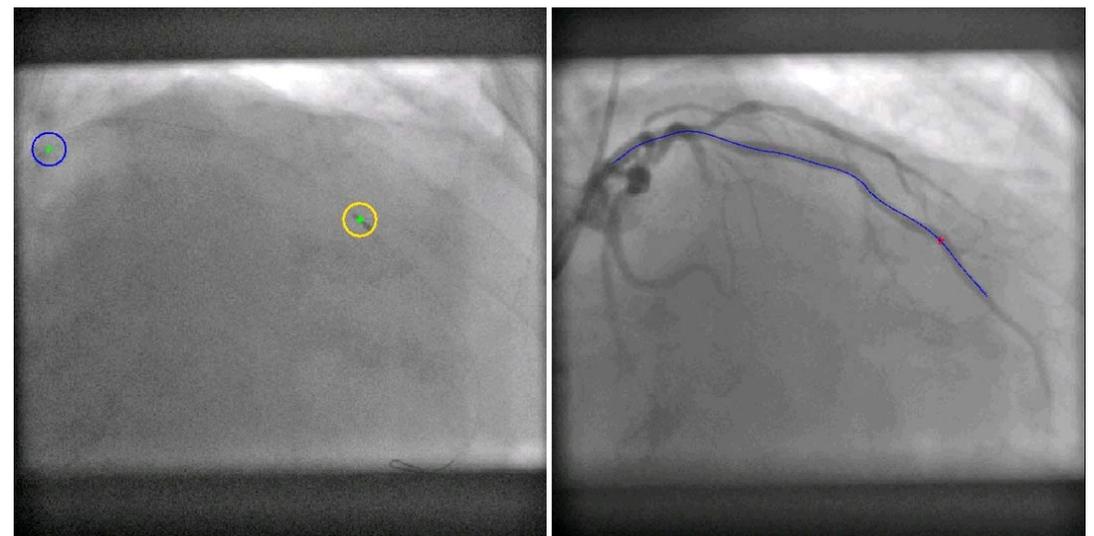
- Mean geodesic error < 1.5

Evaluations (in mm)	mm On training set			Test on 32 cases (trained on other cases)		
	median	mean	std	median	mean	std
IVUS transducer	0.26	0.34	0.56	0.28	0.35	0.32
Guiding catheter tip	0.97	1.58	1.82	1.17	1.92	2.09
Geodesic distance	0.73	1.19	2.14	1.03	1.41	1.51



- Live cases successfully demonstrated in EuroPCR 2011

- The first automatic, simple workflow solution for IVUS/angio or IVUS/CTA co-registration



Conclusion

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- Advantage of Image-based tracking technologies
 - Cheap
 - Simple
 - Hardware acceleration – speed and accuracy improvement
 - Mature algorithms for robust tracking – with the right model and right technology, it can be very robust and integrated in the clinical workflow
- The keys for robustness against large data variation from fluoroscopic sequences
 - Machine learning-based approaches
 - Large data set for training and quantitative evaluation
 - Good models
- Additional advantage –
 - Due to the mature of the technologies → Real clinical applications using image-based tracking methods → Device manufacturers can design the device which is tracked more easily to further spread and improve the use of image-based tracking technology and its applications.

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