Image-Based tracking technologies -

Tutorial of Image guided interventions

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Outline

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

- 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

- 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

- 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)
rapid motion
Long catheter with non-rigid deformation & foreshortening
Overlapping catheters and artifacts
Part or full of the catheter close to image border and moves in & out
**Image-based tracking technology**

- **Needle – rigid wire**
  - Atasoy et al. SPIE Medical Imaging, 2008
  - Heibel et al. ISBI, 2010

- **Guide-wire**
  - 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

- 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

- 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
Step 1: Rigid translation

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

Step 2: Spline optimization

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

\[ = w_1 \int_\C Fds + w_2 \int_\C ds + w_3 (\int_\C ds - L_0)^2, \]

Results: 148/158 frames from 5 image sequences

Similar to Baert et al ‘s work
Guidewire tracking
Heibel et al. CVPR 2009

- 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

- Evaluated on 13 sequences with good results
- Constraint: Bi-plane system required
Catheter Tracking
Ma et al – CS catheter tracking

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

- **Step 2: Catheter detection**

\[
CSCathCost = \sum_{i=1}^{N-2} \cos\theta_i - \frac{1}{N-2} \sum_{i=2}^{N} \left| \text{Blob}_i - \text{Blob} \right|
\]

- **Results:** 18 sequences, 1048 frames

<table>
<thead>
<tr>
<th>Electrode</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low dose images</td>
<td>0.4</td>
<td>0.6</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Normal dose images</td>
<td>0.4</td>
<td>0.8</td>
<td>0.3</td>
<td>0.4</td>
<td>0.3</td>
<td>0.3</td>
<td>0.4</td>
<td>0.4</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

- **Constraints:**
  - Catheter has to have fixed # (10) of electrodes,
  - Catheter cannot bend over 90 degree (foreshortening)
Our methodology - Tracking by robust detection

- 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

State-of-the-Art Technologies:
- Probabilistic Boosting Tree
- Marginal Space Learning
- Robust Tracking Techniques

Annotated Medical Image Databases (2D, 3D, 4D)
Probabilistic Boosting Tree (PBT)

- The probabilistic Boosting Tree
A 2D example: A classifier trained on $p(y)$ can quickly eliminate a large portion (regions 1 and 3) of the search space.
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

- 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

- 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

\[ P(\Gamma_t | Z_t) \propto P(\Gamma_t) P(Z_t | \Gamma_t(u)) \]
\[ \hat{\Gamma}_t = \arg \max_{\Gamma_t} P(\Gamma_t | Z_t). \]

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

\[ Z_t : \text{image observation at the } t\text{-th frame} \]

- Prior model: to impose a smooth movement constraint

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

- Measurement model \( P(Z_t | \Gamma_t(u)) \): to integral the detection scores along the needle shape

\[ P(Z_t | \Gamma_t(u)) = \frac{1}{|\Gamma_t(u)|} \sum_{x_i \in \Gamma_t(u)} P(Z_t | x_i) \]
Coarse-to-Fine Tracking by Kernel Smoothing

- Kernel smoothing of measurements: to obtain a smooth density surface given a number of features (detected segments $x_j$)

  $$P(Z_t|x_i) = \sum_j P(Z_t|x_j^{s}, x_i)P(x_j^{s}|x_i)$$

  $$= \sum_j P(Z_t|x_j^{s})G_{\sigma}(x_j^{s}, x_i)$$

- A Gaussian kernel is used

  $$P(x_j^{s}|x_i) = G_{\sigma}(x_j^{s}, x_i)$$

- Coarse-to-Fine tracking: adaptively change kernel size $\sigma$ in the Gaussian kernel, according to the searching step at each iteration

  Illustration of coarse-to-fine searching of positions

Wang. et al. ISBI 2010
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.

<table>
<thead>
<tr>
<th>Initialization</th>
<th>frame tracking rate</th>
<th>Pixel error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>median</td>
<td>mean</td>
</tr>
<tr>
<td>Full</td>
<td>96.3%</td>
<td>1.31</td>
</tr>
<tr>
<td>Partial</td>
<td>94.6%</td>
<td>1.83</td>
</tr>
</tbody>
</table>

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

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

- **Model** –

- **Detection** –

Wang. et al. CVPR 2009
Formulation of the tracking problem

• The same Bayesian Inference Framework as Guidewire Tracking

\[ P(\Gamma_t(x)|Z_t) \propto P(\Gamma_t(x))P(Z_t|\Gamma_t(x)) \]

• For the guidewire model, we have three different components

\[ P(Z_t|\Gamma_t(x)) = \sum_{x_i} P(Z_t|x_i)P(x_i|\Gamma_t(x)), \]

• \( P(Z_t|x_i) \) is the measurement at individual point, \( P(x_i|\Gamma_t(x)) \) is the weights

\[ P(Z_t|\Gamma_t(x)) = \omega_1 P(Z_t|x_1) + \omega_N P(Z_t|x_N) \]

\[ + \frac{1 - \omega_1 - \omega_N}{N-2} \sum_{i=1}^{N-1} P(Z_t|x_i). \]

• Fusion of multiple measurements
  • Detection measurements + Appearance measurements

\[ P(Z_t|x_i) = P^d(Z_t|x_i)P_d + P^a(Z_t|x_i)P_a \]
Multi-resolution Guidewire Tracking

- Kernel-based measurement smoothing

- Rigid tracking

- Non-rigid tracking
  \[
  E(\mathbf{u}_x) = P(\Gamma_t(x; \mathbf{u}_x)|Z_t) + \alpha \int \left| \frac{d\Gamma_t(x; \mathbf{u}_x)}{ds} \right|^2 dx \\
  + \beta \int \left| \frac{d^2\Gamma_t(x; \mathbf{u})}{ds^2} \right|^2 dx.
  \]

- Result

Wang. et al. CVPR 2009
Guidewire tracking evaluation

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

<table>
<thead>
<tr>
<th>Measurements models</th>
<th>With combined models</th>
<th>With only offline learned models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std</td>
</tr>
<tr>
<td>Overall GW Tracking Prec. (in pixels)</td>
<td>1.80</td>
<td>3.41</td>
</tr>
<tr>
<td>GW Body Tracking Prec. (in pixels)</td>
<td>1.70</td>
<td>2.96</td>
</tr>
<tr>
<td>GW Tip Tracking Prec. (in pixels)</td>
<td>5.45</td>
<td>8.21</td>
</tr>
<tr>
<td>Cath. Tip Tracking Prec. (in pixels)</td>
<td>11.62</td>
<td>12.76</td>
</tr>
<tr>
<td>GW Missing Tracking Rate</td>
<td>9.88%</td>
<td>8.43%</td>
</tr>
<tr>
<td>GW False Tracking Rate</td>
<td>9.62%</td>
<td>6.92%</td>
</tr>
</tbody>
</table>
Catheter tracking in EP procedures

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

- 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

- 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
  - $P(Z_t|C_t) = (1 - \lambda) \cdot P(E_t^*|C_t) + \lambda \cdot P(T_o^s|C_t)$
  - $\lambda = \frac{1}{1 + e^{-f(T_o^s, D(C_t))}}$, $f(T_o^s, D(C_t)) = \frac{\text{cov}(T_o^s, D(C_t))}{\sigma(T_o^s) \cdot \sigma(D(C_t))}$
  - $P(E_t^*|C_t) = \nu_1 P(E_t^*|e_t^1) + \nu_K P(E_t^*|e_t^K)$
  - $+ 1 - \nu_1 - \nu_K \sum_{i=2}^{K-1} P(E_t^*|e_t^i)$
- Online model update

Wu. et al. CVPR 2011
EP Catheters Tracking
Highly noisy data
EP Catheters Tracking
Rapid motion
EP Catheters Tracking

Non-rigid deformation

Wu. et al. CVPR 2011
EP Catheters Tracking
Severe foreshortening
EP Catheters Tracking

Moving out of ROI

Wu. et al. CVPR 2011
EP Catheters Tracking
Partially occlusion, overlapping with cluttered background

Wu. et al. CVPR 2011
Multiple catheters tracking
2 catheters
Multiple catheters tracking
3 catheters
Quantitative Evaluation

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

<table>
<thead>
<tr>
<th>Mean</th>
<th>Median</th>
<th>P85</th>
<th>P90</th>
<th>P95</th>
<th>P98</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
<td>0.5</td>
<td>0.7</td>
<td>0.8</td>
<td>1.0</td>
<td>1.9</td>
</tr>
</tbody>
</table>

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

- Stent visualization via continuous marker and wire detection/tracking
Detect & Track the marker and wire for stent enhancement

Lu. et al. CVPR 2011
Model the wire + markers together

- 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 \( x_1 = x_2 \). \( \delta \) 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

• 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 $\delta$ by a ratio defined by $\|O-M\|_{L_2}$
  - Hypothesis space of $\delta$ becomes:
    $$H_\delta = \{-r, -r + \Delta_\delta, \ldots, 0, \ldots, r - \Delta_\delta, r\},$$
    where $r = 0.36 \times \|O-M\|_{L_2}$

Lu. et al. CVPR 2011
• 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

- 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

- **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

---

*angio acquisition  interactive detection  device detection and tracking  registration*

_Wang. et al. MICCAI 2011_
Evaluation

- Performance

  - Mean geodesic error < 1.5

<table>
<thead>
<tr>
<th>Evaluations (in mm)</th>
<th>mm</th>
<th>On training set</th>
<th>Test on 32 cases (trained on other cases)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>median</td>
<td>mean</td>
<td>std</td>
</tr>
<tr>
<td>IVUS transducer</td>
<td>0.26</td>
<td>0.34</td>
<td>0.56</td>
</tr>
<tr>
<td>Guiding catheter tip</td>
<td>0.97</td>
<td>1.58</td>
<td>1.82</td>
</tr>
<tr>
<td>Geodesic distance</td>
<td>0.73</td>
<td>1.19</td>
<td>2.14</td>
</tr>
</tbody>
</table>

- Live cases successfully demonstrated in EuroPCR 2011

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

Wang. et al. MICCAI 2011
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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